The Dual Nature of Digital Technologies in Health System Overload

Lea Katharina Reis
University of Bamberg

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Erstgutachter: Prof. Dr. Tim Weitzel

Zweitgutachter: Prof. Dr. Thorsten Staake

Mitglied der Promotionskommission: Prof. Dr. Nicolas Rohleder

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Dedicated to my sister,

Elena,

without whose brave career choice I would never have fallen down

the rabbit hole of healthcare research.

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DEDICATION BY PROF. DR. TIM WEITZEL

Informationssysteme (IS) sind ‚schwierig', da sie als soziotechnische Systeme auch das Element „Mensch" umfassen. Sie sind einerseits nützlich, da sie viele Probleme lösen und Chancen, wie etwa flexiblere Lebens- und Arbeitsmodelle, schaffen können. Sie sind andererseits aber auch problematisch, wenn sie entweder gar nicht erst genutzt werden („Reaktanzverhalten") oder ihre Nutzung – in der Regel nicht intendierte – Nebenwirkungen hat, die als Technostress oder „the dark side of IT" beschrieben werden und sich u.a. in reduzierter Arbeitsleistung und psychischen Krankheiten wie Burnout konkretisieren. Diese beiden Seiten aller IS-Medaillen betrachtet Frau Dr. Reis in dieser Arbeit einzeln wie in ihrem – schwierigen – Zusammenspiel. Im Geiste des frühen Wirtschaftsinformatikers Plato, der vor etwa 2.400 Jahren feststellte „*Der größte Fehler bei der Behandlung von Krankheiten ist, dass es Ärzte für den Körper und Ärzte für die Seele gibt, wo doch beides nicht voneinander getrennt werden kann*" reflektiert Frau Reis entsprechend die Chance von IS, zu mentaler Gesundheit beizutragen, Lebenssphären wie Beruf und Familie etwa durch flexible Arbeitsmodelle friktionsärmer zu organisieren oder die Effektivität der Gesundheitsversorgung zu erhöhen. Sie zeigt indes gleichzeitig, dass das Realisieren dieser Chancen ein präzises Verständnis der intendierten und nicht-intendierten Folgen des IS-Einsatzes und ein behutsames Gestalten der entstehenden Trade-Offs mit effektivitätsabträglichen Effekten wie eben Technostress oder Reaktanzverhalten erfordern.

Der Fokus auf IS im Gesundheitskontext ist dabei erfrischend relevant und reflektiert das aktuelle Verständnis der Forschung in der Wirtschaftsinformatik, wie es u.a. in der "Grand Vsion of an ICT-Enabled Bright Society" der Association for Information Systems oder einem aktuellen Überblick über „Recent developments in Business Economics" (Breuer et al., JBE 93 (2023), S. 989–1013) beschrieben ist. So ist ein Hauptergebnis der vorliegenden Arbeit das Aufzeigen, dass rein technische Lösungen – sei es zur Reduktion von Technostress bei flexiblen Arbeitsmodellen oder der Implementierung von KI-basierten Chatbots in Krankenhäusern – nicht ausreichen. Ebenso sind die Gründe, warum Menschen Technostress wahrnehmen oder Technologien wie KI ablehnen zu individuell und kontextspezifisch, um mit einfachen, stammtischfähigen Lösungen erfolgreich sein zu können. Entsprechend ist ein wichtiges (Meta-)Ergebnis dieser Arbeit, das sich durch fast alle Einzelartikel zieht, dass für KI-Implementierungen und die dunkle Seite der IT-Nutzung das u.a. Einstein und Shaw untergeschobene (und in dieser Form auf Umberto Eco aber ursprünglich wohl den Satiriker Henry Louis Mencken im Jahr 1921 zurückzuführende) Bon Mot gilt: „*Für jedes komplexe Problem gibt es eine einfache Lösung, und die ist die falsche*".

Frau Reis adressiert in ihrer Arbeit diese ‚schwierigen' inhaltlichen Herausforderungen mit einem modernen Methodenmix und leistet dabei gleichzeitig Beiträge zur Weiterentwicklung des in der Wirtschaftsinformatik spätestens seit Venkatesh et al. (MISQ 2013) zunehmend populären Mixed-Method-Methodenansatzes, mit dem eine robustere und besser kontextualisierte Theorieentwicklung in der Verbindung qualitativer und quantitativer Methoden gelingen kann durch Ausnutzen der komplementären Stärken und sich nicht überschneidenden Schwachstellen qualitativer und quantitativer Methoden (zB. Nunamaker et al., MISQ 2017). Mit diesem Vorgehen kann sie wichtige Lösungen zu schwierigen Fragestellungen leisten und bestätigt damit den anderen Vor-Wirtschaftsinformatiker Seneca, der 4 Jahrhunderte nach Plato feststellte: *„Nicht weil es schwer ist, wagen wir es nicht, sondern weil wir es nicht wagen, ist es schwer."*

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I would like to take this opportunity to express my deepest gratitude to those people who have accompanied me on my personal and intellectual journey over the past few years, and who have encouraged and enabled me to finally write this dissertation.

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I would also like to thank Prof. Dr. Thorsten Staake and Prof. Dr. Nicolas Rohleder for completing the triumvirate of my PhD committee and for their valuable advice and sincere interest in my work and research.

In addition, I would like to thank my current and former colleagues, many of whom I am proud to call my friends, for their continued support through the ups and downs of writing this dissertation. It has been an honor to work with all of you! I owe special thanks to Prof. Dr. Christian Maier and Dr. Jens Mattke, who always found time to discuss research ideas and possible solutions, and who supported me every step of the way. I feel fortunate and blessed to have them as advisors and an integral part of my academic and personal life.

I would also like to thank my colleagues in the ForDigitHealth team for the fruitful discussions and countless opportunities to present and shape my work.

Last but not least, I would like to thank my parents Edda and Stephan, my sister Elena and my husband Marc! Their unconditional love, endless patience, and tremendous emotional support gave me the confidence and strength to finally complete this dissertation. I am grateful to call you my family and know that we will succeed as a team no matter what challenges life throws at us.

Lea Reis

GERMAN SUMMARY (ZUSAMMENFASSUNG)

“Droht unserem Gesundheitssystem der Kollaps?” (Deutschlandfunkkultur.de 2023). Dieser Frage mussten sich zuletzt zahlreiche Nationen stellen, denn der steigende Bedarf an Gesundheitsleistungen, verbunden mit einer Unterversorgung an qualifiziertem Gesundheitspersonal, ist zum globalen Phänomen geworden (WHO 2023). Um dieser Überlastung des Gesundheitssystems zu begegnen, also Behandlungsbedarfe zu reduzieren und Behandlungskapazitäten zu heben, empfiehlt die Weltgesundheitsorganisation (WHO) zunehmend den Einsatz digitaler Informations- und Kommunikationstechnologien (WHO 2022). Empfehlungen zur Reduzierung der Behandlungsbedarfe fokussieren vor allem die mentale Gesundheit und beinhalten insbesondere die Nutzung sozialer Medien und mobiler Endgeräte, um positive Nachrichten zu empfangen und senden (WHO 2021b) und die Nutzung sogenannter Remote-Technologien zur besseren Integration von Beruf und Privatleben (WHO 2020). Empfehlungen zur Hebung von Behandlungskapazitäten hingegen umfassen vorwiegend den Einsatz künstlicher Intelligenz (KI), mit dem Ziel Ärzte und medizinisches Personal zu entlasten (WHO 2021a). Ob diese Empfehlung allerdings die gewünschten Entlastungseffekte erzielt, bleibt abzuwarten, denn bestehende Literatur im Bereich der Wirtschaftsinformatik zeichnet ein zweideutiges Bild der Rolle von Technologien bei der Überlastung des Gesundheitssystems.

Bezüglich der Reduktion von Behandlungsbedarfen wird, einerseits, von vielversprechenden Anwendungen zur Stärkung und Aufrechterhaltung mentaler Gesundheit berichtet (e.g., Chiauzzi and Newell 2019). Andererseits gibt es Literatur über Stress, ausgelöst oder übermittelt durch digitale Informations- und Kommunikationstechnologien, auch im Kontext der empfohlenen sozialen Netzwerke, mobilen Endgeräte und Remote-Technologien (e.g., Maier et al. 2015), der die Leistungsfähigkeit und das individuelle Wohlbefinden herabsetzt (Benlian 2020; Maier et al. 2019). Individuen, die diesem so genannten „Technostress“ (Ragu-Nathan et al. 2008) über einen längeren Zeitraum ausgesetzt sind, entwickeln ernstzunehmende gesundheitliche Beeinträchtigungen, sowohl psychischer als auch physischer Natur (Becker et al. 2022; Maier et al. 2019), die letztendlich zu einer Mehrbelastung des Gesundheitssystems beitragen.

Bezüglich der Hebung von Behandlungskapazitäten wird in der Literatur das große Potential digitaler Informations- und Kommunikationstechnologien herausgestellt, den Mangel an Gesundheitspersonal zu bekämpfen (Serrano und Karahanna 2016). So können beispielsweise KI-basierte Anwendungen zeitintensive Prozesse, wie Patientenüberwachung und

Dokumentation, unterstützen oder vollständig übernehmen. Dies führt zum einen zu einer Kostenreduktion und setzt gleichzeitig Kapazitäten für andere Bereiche der Gesundheitsversorgung frei (McKinsey 2019). Bisher sind allerdings nur die wenigsten Gesundheitseinrichtungen ausreichend gut ausgestattet, um diese Potentiale tatsächlich zu realisieren (Gartner 2019).

Diese entgegengesetzten Effekte, die digitale Informations- und Kommunikationstechnologien auf das Gesundheitssystem ausüben können, erfordern eine tiefergehende Analyse dahingehend, ob ein verstärkter Einsatz von Informations- und Kommunikationstechnologien tatsächlich empfohlen werden kann und sollte. Eine derartige Empfehlung wäre nur dann akzeptabel, wenn das Gesundheitssystem belastende Nebeneffekte der Technologienutzung minimiert und gleichzeitig zuträgliche Potentiale freigesetzt werden könnten. Die vorliegende kumulative Dissertation folgt diesem dualen Ansatz, basierend auf multiplen Forschungsmethoden in einem Dachpapier und zwölf Forschungspapieren, auf zweierlei Weise:

Zum einen wird im ersten Kapitel, bestehend aus den Papieren I bis V, ein tieferes Verständnis der belastendenden Effekte durch Informations- und Kommunikationstechnologien im privaten Kontext und an der Schnittstelle von privatem und beruflichem Leben erarbeitet. Dazu werden in dieser Dissertation besonders das Stresspotential digitaler Werbemittel in sozialen Netzwerken und auf mobilen Endgeräten und der Arbeit im Homeoffice mittels Remote-Technologie fokussiert. Die erzielten Ergebnisse legen nahe, dass die permanente Konfrontation mit als stressend empfundenen Werbemitteln und die besondere berufliche als auch soziale Isolation beim Arbeiten zu Hause Stressauslöser darstellen. Diese Auslöser können unter anderem zu emotionaler Überlastung führen und die mentale Gesundheit bedrohen. Ein bewusster Umgang mit Anwendungen, die digitale Werbemittel wie Influencer-Marketing oder mobile Werbeanzeigen beinhalten und eine gezielte organisationale Kampagne zur besseren Integration und Motivation der im Homeoffice arbeitenden Belegschaft, können belastende Effekte reduzieren. Darüber hinaus charakterisieren die Ergebnisse einen Kombinationsansatz aus mehreren Gegenmaßnahmen als am effektivsten in der Technostressbekämpfung.

Zum anderen werden im zweiten Kapitel, bestehend aus den Papieren VI bis IX, sinnvolle Anwendungsfälle für KI-basierter Kommunikationsagenten aufgedeckt und anhand relevanter Verhaltensanalysen, Empfehlungen für die erfolgreiche Implementierung zusammengestellt. Diese Ergebnisse identifizieren den Anamnese-Diagnose-Behandlungs-Dokumentationsprozess als gewinnbringenden Anwendungsfall für KI-basierter

Kommunikationsagenten im Gesundheitswesen. Gleichzeitig werden relevante Einflussfaktoren für das Resistenz- und Akzeptanzverhalten von Patienten und Ärzten in diesem Prozess erarbeitet. In beiden Fällen scheitert eine Implementierung nicht an fehlenden Potentialen, sondern an der Furcht vor unvorhersehbaren Konsequenzen, fehlender Nachvollziehbarkeit und überzogenen Vorstellungen bezüglich der Leistungskompetenzen des KI-basierten Kommunikationsagenten. Die Einführung einer Test-KI, die klare Kommunikation von Rahmenbedingungen, Funktionsweise und Einsatzzielen, und die Einbindung von Fachleuten in das Training der KI, steigern die Chance für eine erfolgreiche Implementierung, die zur Entlastung des Gesundheitssystems beiträgt.

Die gewissenhafte Erarbeitung dieser Forschungsergebnisse erfordert einen kombinierten Einsatz multipler Methoden, bestehend aus qualitativen, quantitativen und konfigurationalen Methoden. Dazu haben wir uns an bestehender Mixed-Methods-Forschung zur Kombination verschiedener Forschungsmethoden orientiert (Venkatesh et al. 2013), die bisher allerdings noch keine konfigurationalen Methoden umfasst. In einem dritten Kapitel, bestehend aus den Papieren X bis XII, ergänzen wir existierende Richtlinien dahingehend um einen kondensierten Leitfaden und Anwendungsbeispiele.

Aus diesen Ergebnissen ergeben sich verschiedene Erkenntnisgewinne für die Forschung und Praxis der Wirtschaftsinformatik. Im Hinblick auf die belastenden Effekte durch digitale Informations- und Kommunikationstechnologien erweitern wir bestehende Technostressforschung (Fischer und Riedl 2017; Maier et al. 2019; Tarafdar et al. 2019) durch das neue Unterfeld des Stresspotentials digitaler Werbemittel, spezifische Homeoffice-Stressoren und die Erkenntnis, dass Maßnahmen, die zur Reduktion des Technostresses implementiert werden, auch gegenteilige Effekte haben können. Im Forschungsfeld zu KI-Anwendungen im Gesundheitsbereich (e.g., Laumer et al. 2019) tragen wir, zum einen, sinnvolle Anwendungsfälle für KI-basierten Kommunikationsagenten und, zum anderen, empirisch belegte Empfehlungen zur Implementierung dieser Agenten im Gesundheitswesen bei, basierend auf der Überwindung von Resistenzverhalten. Darüber hinaus tragen wir auch methodisch zur Erkenntnisgewinnung bei, indem wir, in den Papieren X bis XII, bestehende Mixed-Methods-Forschung zur Kombination verschiedener Forschungsmethoden (Venkatesh et al. 2016), um kondensierte Richtlinien und Anwendungsempfehlungen ergänzen.

Zusammengefasst kommt diese Dissertation zu dem Schluss, dass digitale Informations- und Kommunikationstechnologien, bewusst und kontrolliert eingesetzt, einen effektiven Teil der Lösung zur Überlastung des Gesundheitssystems darstellen können.

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Introductory Paper

The Dual Nature of Digital Technologies in Health System Overload:

Empirical Evaluation and Practical Implications

1 INTRODUCTION

Lately, headlines like: “The Coming Collapse of the U.S. Health Care System” (Time Magazine, 10.01.2023) or comparable ones have titled a substantial amount of articles worldwide. In fact, 84 percent of countries report struggling with health system overload, defined as an imbalance between healthcare demand and available supply (WHO 2023). The reasons for health system overload, while manifold, can all be broken down into two core factors: (1) the increase of treatment needs, i.e., more patients, and (2) the decrease of treatment capacities, i.e., less health workforce (Watson et al. 2013). To deal with both core factors, the World Health Organization (WHO) suggests expanding and strengthening the use of digital technologies or information systems (IS) (WHO 2022). Regarding the increase in treatment needs, IS use has foremost the potential to foster and maintain individuals’ mental health (Milne-Ives et al. 2020). Therefore, the WHO suggests, among others, the use of social media, as sending and receiving positive messages lower depressive symptoms (WHO 2021b), the use of mobile applications to support healthy routines (WHO 2020a), and the use of remote technology for better integration of private and work life reducing stress (WHO 2020a); all with the intention to reduce treatment needs and health system overload. To tackle the decrease in treatment capacities, the WHO encourages initiatives to delegate certain health services to cognitive agents (WHO 2021a) due to their potential to relieve the burden on the health workforce (McKinsey 2020). These suggestions sound promising, but whether the intended positive effects of using IS in overcoming health system overload can be realized remains an open question, as existing IS literature paints an equivocal picture of their relation to health and the health system.

Concerning the aim to decrease treatment needs, existing IS literature indeed shows promising use cases where IS use fostered mental health (e.g., Chiauzzi and Newell 2019). Still, it also reveals the burdening nature of IS use on mental health. For example, when using IS in general (Tarafdar et al. 2019b), the recommended social media (Maier et al. 2015b) and remote tools (Weinert et al. 2015a) in particular, individuals can perceive stress, which is either IS-induced or -mediated (Benlian 2020; Ragu-Nathan et al. 2008). This so-called technostress (Tarafdar et al. 2019b) can substantially negatively affect individuals’ well-being, satisfaction, and performance by yielding negative emotions (Beaudry and Pinsonneault 2010; Tarafdar et al. 2010), exhaustion (LePine et al. 2004; Maier et al. 2015c) and burnout (Maier et al. 2015a). When perceived chronically, those technostress consequences eventually impact individuals' mental (Maier et al. 2019; Maier et al. 2022) and even physical health (Becker et al. 2022). Thus, contrasting the intended effects, IS use can contribute to health system overload by "creating" more patients suffering from unhealthy IS use and its consequences.

Concerning the aim to increase treatment capacities, IS literature showcases the supporting nature of IS use. Recent studies show that using IS, such as artificial intelligence (AI)-based applications (Hao 2020; Reis and Maier 2022), has the power to reduce the impact of the health workforce shortage since they lower costs and free resources (McKinsey 2019). Despite those advantages, IS adoption within this industry has happened slower than desired (Agarwal et al. 2010), such that only 22 percent of healthcare facilities are sufficiently equipped to handle the current healthcare demand (Gartner 2019). This leaves us with a situation whereby IS provides the potential to reduce health system overload but has not yet reached a wide-enough-spread use within the industry to realize all associated benefits (McKinsey 2020).

Leveraging both literature streams reveals the dual nature of IS use in health system overload in terms of their equally burdening and supporting effects. Based on those insights, the effectiveness of the suggested IS-based means in decreasing treatment needs and increasing treatment capacities is questionable, and the assessment of whether IS use can and should be recommended to solve health system overload requires further analysis.

Theoretically, according to the logic of double effects (Monge and Hsieh 2020), performing an action to yield positive effects with permission for negative effects is morally acceptable as long as the agent intends the positive effects, does not intend the negative effects, and aims to minimize them, and assesses both effects as proportional to each other. In the context of health system overload, this means that using IS more intensively as a remedy should only be recommended if we can minimize the unintended burdening effects and if the supporting effects are worth the risk of permitting the burden. From the current perspective on health system overload, this is not the case because we do not know enough about the burdening effects of the recommended IS use to minimize them, and the potential benefits of AI cannot outbalance the negative effects due to a lack of actual implementations. Therefore, respecting the logic of double effects when making IS use part of the solution would require a double-barreled approach that simultaneously lowers the burdening effects while unleashing the supporting effects.

To offer such an approach, this dissertation focuses on two research opportunities. First, we want to understand the aspects of using the recommended IS, social media, mobile apps, and remote tools, causing burdening effects on mental health, and find ways to prevent them. So far, prior IS research has centered around IS use in the workplace context (Tarafdar et al. 2019b). We follow initial examples (Maier et al. 2015b; Tarafdar et al. 2020a) and consider aspects of private IS use, particularly of IS-enabled digital advertising in social media and mobile apps, and aspects of IS use in contexts whereby the private and workplace context may intersect, such as remote work, that burden mental health. Second, we want to identify pathways to successfully implement AI-based chatbots in hospitals, unleashing the supporting effects in relieving physicians' workloads. Taking full advantage of the two research opportunities requires the combination of various research methods, including qualitative, quantitative, and configurational approaches. To do so, we consulted the guidelines on mixed-methods research that effectively combine quantitative and qualitative approaches (Venkatesh et al. 2013) but not configurational approaches. While working with these guidelines, we realized there is a need for clearer, condensed guidelines that also allow the combination of configurational methods. This opens a third and methodological research opportunity for this dissertation. Taken together, this leaves us with three main research goals:

Goal 1: Understand how IS use, specifically social media, mobile apps, and remote working tools, causes burdening effects on mental health and how to prevent them.

Goal 2: Identify pathways to successfully implementing AI-based chatbots in hospitals.

Goal 3: Develop condensed guidelines for using mixed-methods approaches within IS research, including qualitative, quantitative, and configurational approaches.

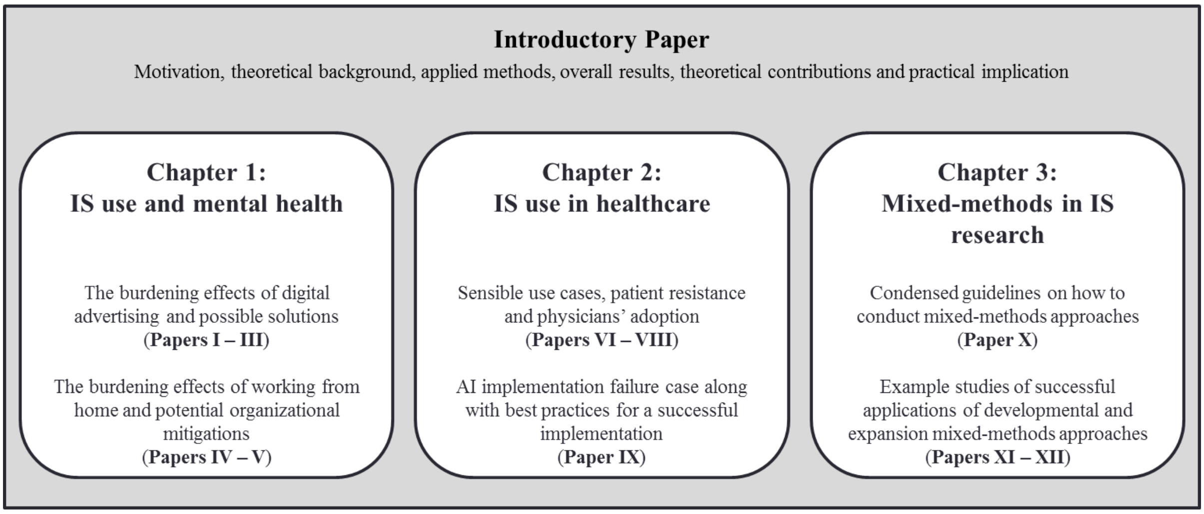

Figure 1. Structure of the Cumulative Dissertation

To achieve those three goals, this cumulative dissertation provides an introductory paper and twelve research papers categorized into three chapters accordingly (see Figure 1). In line with our first goal, **Chapter 1** considers the burdening implications of IS use on mental health, with the aim to prevent them. Specifically, we examine the challenging nature of IS-enabled digital advertising displayed via social media (**Paper I**) and mobile phones (**Paper II**) and consider mobile ad blockers as a remedy to those burdening effects (**Paper III**). Further, we conceptualize and study stress while working remotely (**Paper IV**) and provide evaluated organizational mitigation strategies to protect employees from experiencing technostress (**Paper V**). In **Chapter 2**, we follow our second goal to identify pathways for successfully implementing IS in healthcare, specifically AI-based chatbots in hospitals, to unleash supporting effects. To this end, we first identified sensible use cases for AI-based chatbots for patients and physicians (**Paper VI**). Then, we present drivers of resistance (**Paper VII**) and adoption (**Paper VIII**) of AI-based chatbots for those sensible use cases, followed by an AI implementation failure case, along with best practices on how to implement AI-based chatbots in healthcare facilities (**Paper IX**). To fulfill goal number three, in **Chapter 3**, we provide literature-extracted, condensed guidelines on how to conduct mixed-methods approaches (**Paper X**), along with one example each; of a developmental (**Paper XI**) and an expansion mixed-methods approach (**Paper XII**) involving configurational methods. The overarching **Introductory Paper** is structured as follows: We first present the theoretical background of this dissertation, followed by an outline of our applied qualitative, quantitative, configurational, and mixed research methods. Then, we provide a summary of the research results that have come to light through the twelve papers of this cumulative dissertation and deduce the main theoretical contributions and practical implications. We close with a discussion of limitations and future research directions, followed by a short conclusion.

2 IS USE AND HEALTH SYSTEM OVERLOAD

Health system overload occurs if the available treatment capacities cannot meet the required treatment needs (Abbott 2021). We can distinguish between health system overload in response to a health crisis, such as a disaster or pandemic, referred to as disaster surge, and treatment peaks on a daily basis, referred to as daily surge (Watson et al. 2013). Nowadays, global health systems are confronted with both. According to the WHO, 84 percent struggle with health system overload (WHO 2023). The number of patients is rising, among others, due to an increase in chronic diseases (Ng et al. 2020), longer life expectancy (WHO 2019), and increasing mental health issues related to stress and unhealthy lifestyles (United Nations 2020, 2022). With an estimated shortage of 6.4 million physicians globally, further health workforce leaving healthcare due to economic reasons or post-pandemic burnout, and a large percentage of physicians being aged 55 and older, there are and will not be enough physicians to withstand the required treatment capacities (Abbott 2021; GBD 2019 Human Resources for Health Collaborators 2022; WHO 2021b, 2022). Thus, health system overload might develop from a daily surge to a permanent state.

To fight this development, the WHO and others have called for immediate action and repeatedly advertise using digital technologies (WHO 2022), also called information systems (IS). Still, it is questionable whether the intended positive effects of using IS in overcoming health system overload can be reached, as existing IS literature shows the dual effects of IS use on health and the health system (see Figure 2).

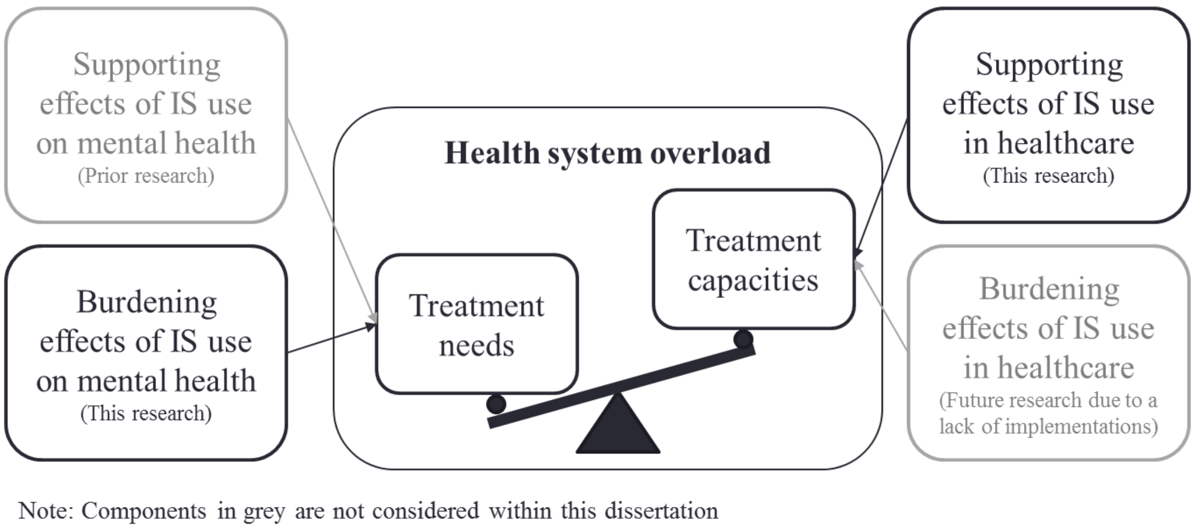

Figure 2. The Role of IS Use in Health System Overload

Regarding the increase in treatment needs, IS use can foster and maintain individuals' mental health (Milne-Ives et al. 2020). Therefore, the WHO suggests, among others, the use of social media to receive positive messages lowering depressive symptoms (WHO 2021b), the use of mobile applications to support healthy routines (WHO 2020a), and the use of remote technology for better integration of private and work life reducing stress (WHO 2020a). Simultaneously, literature provides initial indications of the burdening effects of IS use on mental health, particularly of aspects of using social media, mobile apps, and remote tools (Maier et al. 2015b; Weinert et al. 2015a) that require further investigation to find mitigations. To tackle the decrease in treatment capacities, the WHO encourages initiatives to delegate certain health services to cognitive agents (WHO 2021a) due to their potential to relieve the burden on the health workforce (McKinsey 2020), but actual implementations are rare.

Respecting the logic of double effects (Monge and Hsieh 2020), we should only recommend IS use to overcome health system overload if we can minimize the unintended burdening effects and if the supporting effects are worth the risk of permitting the burden. From the current perspective in literature, this is not the case because we do not know enough about the burdening effects of the recommended IS use on mental health to minimize them and the potential benefits of IS use, such as using AI in healthcare, cannot outbalance the negative effects due to a lack of actual implementations. In line with this logic and drawing from equivocal findings in IS literature concerning the role of IS regarding health system overload (e.g., Serrano and Karahanna 2016; Tarafdar et al. 2019b), this dissertation aims to offer insights into how to make IS use actually part of solving health system overload, by preventing the burdening effects on treatment needs and releasing the supporting effects on treatment capacities.

The following section provides the theoretical background and foundation to achieve this aim. Particularly, in line with the structure of this dissertation, we will present the existing knowledge concerning the burdening effects of IS use on mental health, specifically of using social media, mobile apps, and remote tools, in subsection 2.1. Within this dissertation, we focus on the burdening effects of IS-enabled advertising in social media and mobile apps, particularly influencer marketing and in-app advertising, as well as the burdening effects of remote work. This includes an outline of these research contexts, followed by the theoretical foundation of IS-use-related negative emotions and stress, burdening mental health, including stress mitigation. We also present related research and research opportunities in that field. Subsection 2.2 then focuses on the second pillar of our research, aiming to make IS use part of the solution to health system overload: IS use in healthcare, specifically the potential of AI-based chatbots, to relieve the burden on the health workforce. Likewise, we present the research context of AI-based chatbots in healthcare, the theoretical foundation of behaviors associated with their implementation, and related research and research opportunities.

2.1 IS Use and Mental Health

Mental health refers to a state of overall well-being that enables individuals to effectively navigate the challenges of daily life and contribute productively to their community (WHO 2021b). Common mental health issues include depression, schizophrenia, bipolar disorder, alcohol misuse, and obsessive-compulsive disorder (Brundtland 2000). Furthermore, individuals with mental illnesses are more likely to experience physical heal conditions such as smoking, physical inactivity, a poor diet, obesity, and high blood pressure, underscoring the importance of managing one's mental well-being (Prince et al. 2007). In the last three years, the number of people suffering from mental health problems, such as depression or anxiety, reached an all-time high (WHO 2021b). In the US alone, the reported number of adults suffering from depression rose from 11 percent in 2019 to 42 percent in late 2020 (Abbott 2021). Unfortunately, the availability of mental health professionals has remained insufficient. Globally, there is less than one mental health professional for every 10,000 individuals, leaving many mental health issues unaddressed (United Nations 2020). Even in industrialized countries like the US, half those in need do not receive treatment (Mental Health America 2021). With rising numbers of patients and a lack of skilled personnel, the global health system cannot cope with the current demand for mental health treatment (United Nations 2020). The consequences of untreated mental health problems are significant, with individuals experiencing severe mental health conditions facing a life expectancy 10-20 years shorter than the general population (WHO 2020b). Moreover, the global economy bears a heavy burden, exceeding one trillion dollars annually, due to unattended mental health problems and their associated impacts (United Nations 2020).

One way to cope with skill shortage and rising mental health treatment demands is using IS, either to free resources and help mental health professionals work more efficiently (Reis and Maier 2022) or to support individuals in fostering and maintaining their mental health. This includes, for example, a more intense use of mobile devices and social media to promote and receive positive and hopeful stories and content (WHO 2021b). Another possibility is to use IS to enable remote work, allowing individuals to realize higher flexibility in working hours (Suh and Lee 2017) and a better integration of work and private life (Allen et al. 2021), which both foster self-care and mental health. Indeed, 50 percent of adults in the US reported using mobile devices and social media more often within the last three years (eMarketer 2020), and 85 percent of candidates only want to apply for remote, flexible jobs. However, this in itself can become a risk to individuals' mental health. Within IS research, it is abundantly clear that there is a potentially stressful aspect to IS use in general (Ragu-Nathan et al. 2008; Tarafdar et al.

2019b); mobile devices (Ardèvol-Abreu et al. 2022) and social media in particular (Maier et al. 2015b). Also, two out of three employees state that working from home has drawbacks, including increased isolation, loneliness, and difficulty disconnecting from work (Robinson 2021), all of which can place burden on mental health. Additionally, the use of mobile devices and mobile apps makes individuals vulnerable to less researched types of IS-transmitted stress, such as stress resulting from receiving digital advertising while browsing social media or using a mobile device (McGrath 2019). In the following, we will outline the different contexts potentially burdening mental health that are considered within this dissertation, followed by the theoretical foundation of IS-related stress burdening mental health and an overview of related research in that field.

2.1.1 Contexts of IS Use Burdening Mental Health

IS use can burden mental health in various ways, including negative emotions and stress from different IS use contexts, including the recommended IS to foster mental health (WHO 2021b). Specifically, we focus on influencer marketing in the context of social media use, in-app advertising in the context of mobile device use, and remote work. We will outline the contexts considered in this dissertation in the following.

2.1.1.1 Research Context: Influencer Marketing

Social media marketing has become a key pillar for companies to reach current and potential consumers, as it offers unique features like immediate interaction with social media users (Mattke et al. 2017b), social feedback mechanisms (Mattke et al. 2020d), and the possibility for directed endorsement (Mattke et al. 2019). Advertising through endorsement, referring to the purposeful recommendations persuading users to purchase an advertised product online and offline, has reached an all-time high with the emergence of influencer marketing (van Reijmersdal et al. 2020). Social media influencers are individuals with a sizable social network who shape users' attitudes towards brands and products through apparent independent endorsements (De Veirman et al. 2017; Müller et al. 2018a). Recent statistics show that 40 percent of social media users purchase products endorsed by influencers, generating eleven times as much return on investment as traditional marketing (Digital Marketing Institute 2020; ifluenz 2020). Influencer marketing does not only pay off for companies, which have spent more than $9.7 billion on influencer marketing globally in 2020 (Blagojević 2021), but also for the influencers, who, in the same year, earned on average $5-$15 per 1000 followers per post (Wandiger 2020).

The key asset for influencers to serve as professional endorsers in the marketing industry is self-branding, so advertising their person and lifestyle to attract users' attention (Khamis et al. 2017). Therefore, influencers construct social media accounts centered around themselves that present the good side of life, including exclusive access to products and events, glamorous vacations and activities, and overly perfect bodies and beautiful faces (Khamis et al. 2017; Marwick 2015). Simultaneously, they present themselves as ordinary people, showing their lives "as lived" and creating intimacy through engagement with their followers to make them reachable (Chae 2018). In short, these accounts aim to create the picture of everyday people who own the things people dream of, or the life they desire to live (Marwick 2015), which might lead to the evaluation of users' situation compared to these profiles, otherwise referred to as social comparison (Lewallen and Behm-Morawitz 2016). This constant comparison can yield negative emotions, like envy (Chae 2018), and burden users' mental health in the long run.

2.1.1.2 Research Context: In-App Advertising

In-app advertising entails displaying advertisements or marketing messages within mobile applications on various mobile devices like smartphones or tablets (Kovalenko 2022; Mattke et al. 2021a). Given that approximately 88 percent of smartphone usage time is spent on mobile apps (BuildFire 2022), in-app advertising offers several advantages to advertisers. These advantages include a vast advertising audience due to the high app usage times, reduced ad-blocking possibilities, and the ability to conduct more effective and personalized targeting based on a precise understanding of app users' interests and habits (Rafieian and Yoganarasimhan 2021). Enhanced targeting leads to increased click-through and conversion rates and promises higher ad revenue for advertisers and app developers (Desaulnier 2017) while delivering more relevant and valuable ads to app users (Mattke et al. 2021a). While early studies have studied the positive effects of in-app advertising, resulting from a higher entertainment value, informativeness, and credibility (Çiçek et al. 2018; Raines 2013), the latest research (Gao et al., 2022) shows that app users are overwhelmed with the amount and frequency of in-app ads, annoyed by the inability to skip, invasiveness and interruption that adds cause, and overall frustrated with their app usage experience. Consequently, two out of three app users considered at least once uninstalling the app to escape the intrusive and exhausting in-app environment (Gao et al., 2022). Such negative emotions and the resulting exhaustion point to a stress reaction to in-app advertising, which could also affect app users' mental health.

2.1.1.3 Research Context: Remote Work

There is a lack of consensus on the definition of remote work, also known as working from home or telework, across different academic fields (Carillo et al. 2021). Most definitions encompass two key characteristics: 1) using IS for work and 2) physical separation from the traditional workplace. The role of IS in remote work varies, ranging from using them to stay connected while working at a distance from the workplace (Bélanger and Allport 2008) to restructuring the way of working remotely (Baker et al. 2006). Remote work provides benefits for employees and organizations. Fewer distractions allow employees to work more efficiently, raising organizations' productivity (Bloom et al. 2015). Higher flexibility in working hours (Suh and Lee 2017) and better integration of work and private life (Allen et al. 2021) enable equal opportunities for men and women to develop their careers by balancing family and job demands more effectively (Greenhill and Wilson 2006). The increased autonomy and trust expressed through the possibility of doing remote work increases employees' job satisfaction (Waizenegger et al. 2020), resulting in fewer job turnover intentions (Igbaria and Guimaraes 1999). In contradiction, literature has identified various drawbacks related to remote work, such as constant connectivity to work in non-work hours (Derks et al. 2016) and the pressure to reply to demands (Matusik and Mickel 2011). Moreover, remote work can lead to emotional strain due to the proximity of home and work, resulting in fatigue, negative emotions (Sonnentag et al. 2008) and a constant distraction from private life and family (Allen et al. 2015). General work stress literature shows that such circumstances can adversely affect employees' well-being, such as yielding exhaustion (Moore 2000) and stress (Ahuja et al. 2007), burdening their mental health.

2.1.2 Theoretical Foundation of IS-Use-Related Negative Emotions and Stress Burdening Mental Health

Now that we understand that each of the considered IS use contexts potentially offers burdening effects on individuals' mental health, we need to clarify if and how these adverse effects occur and influence individuals' mental health. To this end, we outline the theoretical foundation of IS-use-related negative emotions and stress in this subsection.

2.1.2.1 IS-Use-Related Negative Emotions and Stress

Stress is a transactional process that translates demanding stimuli, perceptions, or situations, called stressors, into adverse emotional or psychological reactions, called strain (Lazarus and Folkman 1984). In general, stress arises when individuals perceive a discrepancy between the demands of a situation and their ability or resources to emotionally or cognitively deal with it (Folkman 1984). If individuals are emotionally overextended, they show an aversive, potentially harmful, and unconscious psychological strain reaction described as emotional exhaustion (Wright and Cropanzano 1998). Emotional exhaustion is manifested by physical fatigue and feeling psychologically and emotionally drained (Wright and Cropanzano 1998) and is associated with bad mental health conditions, such as burnout and depression (Seidler et al. 2014). The stressors leading to emotional exhaustion across contexts are manifold. Since we are especially interested in specific IS use contexts, in the following, we focus on IS-use-related stressors as a base for theorizing the burdening effects of IS-enabled digital advertising and remote work. To this end, we next outline the principles of IS-use-related stress, also called technostress (Ragu-Nathan et al. 2008), and its potential to cause emotional exhaustion and other psychological strains that burden mental health.

Technostress. Technostress refers to stress resulting from IS use and, in line with the transactional definition (Lazarus and Folkman 1984), encompasses the translation of techno-stressors into techno-strain (Ayyagari et al. 2011). When using IS, individuals encounter various techno-stressors (Fischer et al. 2021; Maier et al. 2015b; Maier et al. 2022; Ragu-Nathan et al. 2008) that either challenge or hinder the individual (LePine et al. 2004). While challenging techno-stressors can increase individuals performance and creativity (Eckhardt et al. 2013), hindering techno-stressors are associated with adverse effects on individuals' performance, satisfaction, and well-being (Pirkkalainen et al. 2019; Srivastava et al. 2015; Tams et al. 2018), which matches the focus of this dissertation. Techno-stressors are sensitive to particular IS use contexts (Maier et al. 2015b; Tarafdar et al. 2019b) and have been foremost studied in the workplace context. Here, previous research has highlighted five techno-stressors in particular (Pirkkalainen et al. 2019; Srivastava et al. 2015): Techno-complexity (referring to the feeling of inadequacy in dealing with intricate and interconnected systems), techno-insecurity (involving the fear of being replaced by IS, leading to job insecurity), techno-uncertainty (alluding to the struggle with one's ICT capabilities and constantly changing systems), techno-invasion (defined as the experience of privacy intrusion when using IS), and techno-overload (relating to feeling overwhelmed by the sheer volume of requests and information) (Ragu-Nathan et al. 2008). The identified techno-stressors lower individuals' performance and job satisfaction (Tarafdar et al. 2010) and foster turnover intentions due to reduced organizational commitment (Ragu-Nathan et al. 2008) and burnout (Maier et al. 2015a). In the less-researched private context, existing studies have primarily focused on social-media-use-related stress, including social-media-specific stressors and consequences (Maier et al. 2015b; Maier et al. 2015c; Tarafdar et al. 2020a), which we will outline next, due to its particular relevance for the scope of this dissertation.

Social-Media-Use-Related Stress. Social media's primary function is exchanging messages and posts with one’s social network (Maier et al. 2015b). While this provides advantages in terms of low-threshold stay-in-touch-opportunities (Mattke et al. 2020d), the compulsory use of social media, the sheer amount of information, and constant confrontation with the life of others can cause stress, adverse emotional reactions, such as envy or frustration, and exhaustion (Dhir et al. 2018; Krasnova et al. 2015; Maier et al. 2015b). These adverse effects are partly related to the socially demanding environment created by the constant confrontation with new information about one's social network (Maier et al. 2015b) and partly to the ongoing evaluation of one's own situation compared to the presented lives of others, short: social comparison (Chae 2018).

Social comparison theory (Festinger 1954) describes two types of social comparison: upward and downward. Downward comparison refers to individuals comparing themselves with those less fortunate or inferior in status, attributes, or capabilities (Lewallen and Behm-Morawitz 2016). Even though individuals may not see this comparison process as morally commendable nor desire the misfortune of others, it brings significant psychological benefits. When people realize that their own life or situation is not as bad as someone worse off, they experience relief and improved well-being, prompting them to engage in this comparison, even if they do not actively seek it (Wills 1981). On the other hand, upward comparison occurs when individuals compare themselves to someone superior whose status, attributes, or capabilities are seen as attainable (Lewallen and Behm-Morawitz 2016). While upward comparison can motivate self-improvement, poor self-evaluation can lead to negative emotions like frustration or envy and, eventually, low self-esteem. Such feelings burden individuals’ mental health and can accelerate and intensify symptoms of depressive disorders (Steers et al. 2014; Vogel et al. 2014). The standard for comparison, or in other words, the person to compare with, is usually someone from one's close social network, such as a friend, a co-worker, or a family member. Still, strangers or celebrities presented in the media can also function as a standard for comparison if their situation, status, or attributes seem generally achievable (Haferkamp and Krämer 2011). Social comparison is a universal phenomenon in various social contexts, including social media. Overall, the potential for upward comparison in social media is exceptionally high, as users tend to present primarily positive aspects of their lives (Marwick 2015), increasing the chance for a potentially poor self-evaluation and the associated consequences for mental health.

2.1.2.2 IS-Use-Related Stress Mitigation and Coping

Part of understanding the burdening effects of IS use on mental health is how to prevent and overcome them. Literature treating the prevention and reduction of stress can thereby be divided into two sub-streams: literature on stress coping, treating emotional, cognitive, or behavioral effort to better handle experienced stress, and literature on stress mitigation, examining actions aiming at the reduction, tolerance or recovery from stress (Salo et al. 2017).

Stress coping. When individuals encounter stressors and perceive strain, they respond with coping. Coping describes behavioral, cognitional, and emotional efforts to handle, reduce, or tolerate the threatening demand (Folkman 1984), regardless of their success in lowering strain (Latack and Havlovic 1992). Coping can be either reactive, when individuals already experience strain, or proactive, in response to stressors to prevent strain. To choose a coping strategy, individuals undergo a cognitive appraisal process, including primary and secondary appraisal. In primary appraisal, they first estimate the threat posed by the demand, and in secondary appraisal, they assess their ability to deal with it effectively (Skinner et al. 2003). The numerous resulting coping strategies can be categorized based on their focus and methods (Latack and Havlovic 1992; Skinner et al. 2003). One way to classify coping strategies is the problem-emotion distinction; Problem-focused strategies aim to address and solve problems related to stressful situations, while emotion-focused strategies primarily manage or regulate the emotions arising from stressful situations (Folkman 1984). Individuals tend to choose problem-focused coping when they perceive their situation as changeable and emotion-focused coping when they see it as unchangeable (Folkman 1984). Within the chosen focus of coping, coping methods can be further classified as control versus escape coping methods (Latack and Havlovic 1992). Control strategies involve a proactive, take-charge approach, whereas escape strategies involve distancing oneself physically or emotionally from the stressful situation. Both control and escape coping methods can focus on the problem or the emotions in stressful situations (Latack and Havlovic 1992).

Stress mitigation. Research has explored stress mitigations; actions that aim to change demanding situations in various contexts, including job stress, war stress, and technostress (Pflügner et al. 2020; Salo et al. 2017; Valta et al. 2021). We can distinguish different types of technostress mitigations along three dimensions. First, we can differentiate which part of the transactional stress model (Lazarus and Folkman 1984) is targeted by the mitigation. The mitigation either aims to actively reduce or prevent a techno-stressor, or enable the techno-stressor to be tolerated such that it impedes the transaction into techno-strain or tackles techno-strain recovery (Salo et al. 2017). Second, we can distinguish who initiates the mitigation, so whether the mitigation is anchored with the confronted individuals themselves, is organizationally orchestrated, or steams from the actual IS use (Pflügner et al. 2020; Pirkkalainen et al. 2019). Third, we can differ in the content of the mitigation, so whether the action aims at yielding behavioral changes or changes related to the potentially stressful environment (Latack and Havlovic 1992), which has, so far, been treated less in technostress research.

2.1.3 Related Research and Research Opportunities

Based on the described research contexts and theoretical foundations, we present related research treating the burdening effects and possible mitigations and coping strategies within the contexts of influencer marketing, in-app advertising, and remote work. From there, we deduce specific research opportunities.

2.1.3.1 Related Research and Research Opportunities: Burdening Effects of Influencer Marketing, In-App Advertising and Remote Work

The intensified use of IS entails the risks of burdening individuals' mental health through negative emotions and technostress, which has received increasing attention in IS research over recent years (Fischer and Riedl 2017). Here, we specifically focus on the stress potential of IS-enabled digital advertising options, such as influencer marketing in social media and in-app advertising on mobile apps, and the stress potential of remote work. While existing research has neither touched the stress potential of IS-enabled digital advertising nor identified specific remote work stressors, we can still outline related literature to frame our research scope and deduce research opportunities.

Concerning the stress potential of influencer marketing, existing research shows that, besides the adverse effects resulting from using social media itself (Maier et al. 2015b), the content users receive from their social network can trigger upward comparison and the associated negative emotions, such as envy and frustration (Krasnova et al. 2015). The possibility of social media content triggering upward comparison is exceptionally high since users generally tend to present the best, socially most desirable version of themselves (Chou and Edge 2012). Today, the social network that users create through social media, is no longer limited to people they know. They are also exposed to individuals, who openly share their lifestyles and activities to promote brands or products, known as influencers. While recent research has demonstrated that influencers can serve as a reference for upward comparison (Chae 2018), the potential impact of exposure to influencer posts on mental health and symptoms of depressive disorders has not been explored, yet. Within **Paper I** of this dissertation, we want to take the opportunity to explain if the confrontation with influencers and their lifestyle can be considered a stressor that yields strain and how it eventually affects users' mental health.

Concerning the stress potential of being exposed to IS-enabled digital advertising when using mobile devices, neither IS nor advertising research has examined digital advertising stress in general or in-app advertising stress in particular. Still, there are practical indications that individuals perceive stress when dealing with it (McGrath 2019) due to the negative perceptions of the exposure to in-app advertising. Individuals perceive in-app advertising as stressful due to its high frequency and unwanted interaction, making it interruptive and privacy-invading. These perceptions leads to negative emotions, such as annoyance and frustration, which can cause users to feel overwhelmed and exhausted (Gao et al. 2021; Gao et al. 2022; Rafieian and Yoganarasimhan 2021). Based on prior considerations in other contexts (Boswell et al. 2004; Tarafdar et al. 2010), we can classify app users' negative perceptions of in-app advertising as potential stressors since they evoke strong emotional responses. However, which potential stressors are appraised as stressful and can be considered in-app advertising stressors remains unexamined. Further, literature considers overwhelming emotional reactions, resulting in emotional exhaustion, a psychological strain (LePine et al. 2004; Maier et al. 2012). Based on the reported findings in advertising literature (Gao et al. 2022), this strain could also apply to in-app advertising stress. In light of the rising popularity of in-app advertising and the potentially harmful consequences of in-app advertising stress, **Paper II** aims to understand whether in-app advertising causes stress and identify related in-app advertising stressors and strain.

Regarding specific remote work stress, the literature emphasizes that, compared to on-site employees, remote workers are more susceptible to experiencing stress-related symptoms impacting their mental health (Mann and Holdsworth 2003). This influx of stress could be attributed to certain factors unique to remote work, such as increased social and professional isolation (Golden et al. 2008; Mulki and Jaramillo 2011) and less interaction with colleagues (Bloom et al. 2015). In recent years, there has been a growing interest in researching the relationship between remote work and stress (Adamovic 2022; van Zoonen et al. 2021). These studies have established that remote work is indeed stressful, but they have not specifically identified the stressors or adverse consequences explaining this stress. Instead, they often draw from related research on general work stress (Ahuja et al. 2002) or stress related to IS use while working remotely (van Zoonen et al. 2021) to explain the accumulation of stress-related symptoms among remote workers. One possible explanation they suggest is that remote workers experience stress from both work-related factors and IS-related factors (Maier et al. 2015a), which arise due to the necessity of using technology while working remotely, leading to exhaustion (Ayyagari et al. 2011; Moore 2000; Podsakoff et al. 2007). Other explanations associate employees' perception of stress primarily with traditional work stressors, such as workload, role overload, and work-home conflict, along with their related consequences like work exhaustion and reduced job satisfaction, organizational commitment, and performance (Ahuja et al. 2002; Golden et al. 2008). These explanations hold for remote and on-site work (Ahuja et al. 2007). Simply transferring existing work stressors and their consequences identified in previous work stress literature (Ahuja et al. 2007) to the context of remote work provides only a limited understanding of how specific characteristics of remote work, such as the discussed isolation (Golden et al. 2008), influence employees and their perceived stress related to remote work. Still, these specific characteristics of remote work are crucial for comprehending their impact on employees (Carillo et al. 2021). For instance, existing research indicates that the amount of time spent working remotely influences employees' perceptions of adverse effects related to remote work (Golden et al. 2008). This suggests that certain perceived stressors and their associated consequences might intensify or diminish with prolonged remote work. Additionally, research has shown that the circumstances and characteristics of remote work during the pandemic differ from pre-pandemic remote work, as remote work has shifted from a voluntary choice to a mandatory full-time practice (Carillo et al. 2021; Waizenegger et al. 2020). These changes may also impact how employees perceive remote work stressors and associated adverse consequences, potentially leading to an increasing perception of stress related to remote work since the pandemic (Saura et al. 2022). Current literature fails to answer these questions, as it does not delve into the specific remote work stressors and associated adverse consequences unique to remote work. **Paper IV** takes on the challenge of doing so.

2.1.3.2 Related Research and Research Opportunities: Possible Mitigations and Coping Strategies for the Treated IS Use Contexts

Since related literature has, so far, failed to conceptualize or carve out the specifics of stress related to IS-enabled digital advertising or remote work, it also lacks mitigations and coping strategies tackling those kinds of stress. Still, there is related literature to build on, which we will use to deduce particular research opportunities in coping and mitigations.

While coping in response to work stress (Cavanaugh et al. 2000; Latack and Havlovic 1992) and technostress coping has received increasing attention over the last years (Pirkkalainen et al. 2019; Tarafdar et al. 2020b; Weinert 2018), coping in response to IS-enabled digital advertising has yet to be examined. Considering the foundation of coping research and based on the provided classification of coping responses, problem-focused strategies in tackling stress related to IS-enabled digital advertising concentrate on reducing or stopping the confrontation with ads. In contrast, emotion-focused strategies focus on being less emotionally affected by them. In influencer marketing, this would incorporate efforts to impede upward comparison in response to influencer posts (Chae 2018), which **Paper I** aims to uncover. In the in-app advertising context, literature considers uninstalling apps (Gao et al. 2022). Based on insights from existing technostress research (Califf 2022; Maier et al. 2015c), discontinuing app usage can be a coping strategy, but whether users employ this strategy to regain control over the situation or escape from the stress caused by in-app ads remains unclear. Moreover, there is a separate body of literature on ad avoidance (Cho and Cheon 2004; Edwards et al. 2002; Mattke et al. 2018b; Mattke et al. 2018c), which, based on our understanding of stress literature (Folkman 1984; Latack and Havlovic 1992), can be considered an emotion-focused coping strategy to deal with advertising stress. Ad avoidance may diminish the effectiveness of advertising (Müller et al. 2018b; Müller 2019), but it does not necessarily reduce the potential advertising audience or influence the delivery or display of in-app ads, as users do not actively engage with or pay attention to the ads. Literature presents ad-blocker usage as a means to reach the desired distance to ad exposure and switch to a better, ad-free situation (Mattke et al. 2017a; Meier et al. 2021; Müller et al. 2017). The possibility for ad-blocker usage within apps is limited (Rafieian and Yoganarasimhan 2021). Therefore, **Paper II** aims to identify other, primarily problem-focused, coping strategies in that field. Nonetheless, given the broader context of stress in response to IS-enabled digital advertising in general and leaking insights concerning stress potential and mitigations, **Paper III** takes on the opportunity to tackle the motivations behind ad-blocker usage in response to challenging ads on mobile devices.

Regarding mitigations, the literature has neither identified specific ones in the context of IS-enabled digital advertising nor remote work (which we aim to do in **Paper II** and **Paper IV**). However, there is literature on specific technostress mitigations (Salo et al. 2017; Tarafdar et al. 2015) in the organizational context (Pflügner et al. 2020). Traditionally, research on organizational mitigations has focused on overall technostress rather than specific strategies to address individual techno-stressors (Valta et al. 2021). Indeed, those mitigations implemented by organizations, such as providing technical help for users through help desks, facilitating the sharing of technical knowledge and training, and encouraging user involvement have been found to reduce techno-stress levels in general (Tarafdar et al. 2015). Additionally, organizations can help employees manage work-home boundaries to ease the strain caused by techno-stressors (Benlian 2020). Recent literature has delved more into how certain measures effectively mitigate specific techno-stressors (Valta et al. 2021). For instance, cognitive behavior skills training has been shown to help employees cope with techno-overload in email communication (Soucek and Moser 2010). Implementing technical solutions for interruption control allows users to manage the timing of responding to IS-transmitted information and thereby helps control techno-overload (Galluch et al. 2015). Creating contact persons and encouraging mutual support to resolve technical issues effectively reduces techno-overload while minimizing email traffic proves most effective in mitigating techno-invasion (Gaudioso et al. 2017). Since research indicates that sometimes a general approach to technostress is not equally effective in reducing different techno-stressors, there is a need for organizations to implement measures specifically tailored to address certain techno-stressors (Pflügner et al. 2020; Valta et al. 2021). **Paper V** wants to take advantage of this opportunity. Using the example of organizational mitigations to techno-invasion and techno-overload, specifically related to managing work-related information and communication transmitted via IS, **Paper V** aims to contribute to techno-stressor mitigation research in three primary ways. Firstly, while existing studies have mainly focused on organizationally implemented technological measures, this research explores other dimensions beyond technology that may offer opportunities to address techno-invasion and techno-overload (Pflügner 2022). It aims to consider cultural and social contexts as essential elements of technostress mitigation beyond merely fostering social support. Secondly, most existing research has taken an organizational perspective examining technostress among non-IT professionals (Tarafdar et al. 2015). This study seeks to gain valuable insights by considering the views IT professionals, who face unique challenges due to constant connectivity with work and work-family conflicts (Maier et al. 2015a; Moore 2000). Further, IT professionals often shoulder significant responsibilities for their organizations' digital infrastructure and may experience increased workloads. Thirdly, by considering the employee perspective, the study aims to analyze potential unintended and harmful side effects of measures introduced to mitigate technostress. It acknowledges that organizational mitigation measures may inadvertently restrict employees' workday organization and flexibility, leading to adverse effects, such that a block of emails after hours results in an increased perceived techno-overload the following workday (Gibson 2014). Understanding such unintended adverse effects is vital for both organizations and employees, as they can affect mental health and well-being, counteracting the purpose of reducing techno-stressors.

Overall, based on the theoretical foundation of (techno-) stress and mitigations, **Papers I to V** want to take advantage of the opportunity to understand and conceptualize the burdening effects resulting from intensive IS use in the contexts of IS-enabled digital advertising in social media and on mobile devices and remote work. This includes examining possible ways and measures to fight these burdening effects and understanding the potential downsides to these approaches. All of these opportunities reveal paths to reduce or prevent the burdening effects of IS use and to make IS use part of the solution to health system overload. The same applies to the successful integration of IS to relieve the health workforce, which we outline next.

2.2 IS Use in Healthcare

The second pillar of our research aims to make IS use part of solving health system overload through understanding the supporting effects of IS use to relieve the health workforce. Over the last few years, IS use in healthcare has significantly grown in applications and functionality (Heavin 2017). However, healthcare is among those industries that cannot draw upon a long history of IS integration (McKinsey 2019). For example, by 2019, 97 percent of healthcare facilities had successfully integrated functional electronic health record (EHR) systems to organize patient data (Monica 2019). Whilst just five years earlier, a mere 44 percent of healthcare facilities had implemented a basic support system for admitting new patients, and just one in eight had adopted an EHR system (Peng et al. 2014). Despite this progress in some areas of healthcare, the adoption of IS aimed at improving healthcare provision, such as clinical decision support systems and telehealth, has not yet reached a satisfactory level and actually happens slower than desired (Agarwal et al. 2010; Payton et al. 2011; Reddy 2019). In fact, industry reports suggest that without significant changes in their IS infrastructure, most healthcare facilities may struggle to meet future healthcare demands (McKinsey 2020), with only 22 percent currently equipped to handle the existing pressures (Gartner 2019).

Paper	Infor-mation system	Perspective		Major findings
		Physi cians	Pa-tient	
2007				
Bhattacherjee and Hikmet (2007)	EHR	X		Distrust as a driver of adoption failure
Mantzana et al. (2007)	EHR	X		Adoption is not easy, as it affects patients' lives, actors are important.
Reardon and Davidson (2007)	EHR			The inclusion of small practices enables the full benefits of EHR
2009				
Angst and Agarwal (2009)	EHR		X	Privacy Concerns in EHR adoption, Elaboration
Ayal and Seidman (2009)	EHR	X		Satisfaction of employees was raised through EHR
Jensen et al. (2009)	EHR		X	Implications for field, organization and individual cooperation
2010				
Agarwal et al. (2010)	EHR	X	X	Adoption guidelines
Holden and Karsh (2010)	EHR	X		Established models are not sufficient for healthcare
2011				
Kane and Labianca (2011)	EHR	X		IS avoidance risks the implementation success
Ozdemir et al. (2011)	EHR			Personal EHR can provide benefits as they do not have switches in systems
2012				
Mishra et al. (2012)	EHR	X		Physician identity foster assimilation

Nov and Schecter (2012)	EHR	X		Physicians show a dispositional resistance to change to EHR
2014				
Peng et al. (2014)	EHR	X		Slow healthcare IS adoption
Silsand and Ellingsen (2014)	EHR	X		Participation of personal in implementation fosters use
Strong et al. (2014)	EHR	X		Affordance-based change management for multilevel process change
2015				
Yaraghi et al. (2015)	EHR			Adaption use and value co-production of data sharing
2016				
Findikoglu and Watson-Manheim (2016)	EHR	X		Linkage of macro-level goals and micro-level behavior is needed to enable adoption in developing countries
Kohli and Tan (2016)	EHR	X		Stakeholders' issues that must be addressed to develop and deploy EHR.
2017				
Ayabakan et al. (2017)	EHR			Data sharing reduces duplications in medical data
Baird et al. (2017)	EHR			Long term assimilation of processes and administration
Bernardi (2017)	EHR		X	HealthIT can foster human development and healthcare
Lin et al. (2017)	EHR			Multitask approach recognizes multiple adverse effects in chronic diseases
Pinsonneault et al. (2017)	EHR			Quality improvement and cost reduction
Tong et al. (2017)	EHR	X		Social power and administrative work shape indirect use
2018				
Adjerid et al. (2018)	EHR			Financial incentives and mature systems have a positive effect on decrease
Fox and Connolly (2018)	Mobile health		X	Digital divide in mobile health use
Kwon and Johnson (2018)	EHR			Meaningful-use fosters security performance
Romanow et al. (2018)	EHR		X	Impacts of EHR use for patients
2019				
Brohman et al. (2019)	Tele-health		X	Feedback of patients valuable for tele-monitoring
Kim and Kwon (2019)	EHR		X	Security risks of EHRs
Klecun et al. (2019)	EHR	X		Stakeholder integration is difficult, top-down attempt necessary
Lin et al. (2019)	EHR			Meaningful use and readiness of processes positively affect the quality
Murungi et al. (2019)	EHR	X		Distrust in the system limits adoption
Yaraghi et al. (2019)	EHR		X	Patients do not solely trust their physician in disclosing
2020				
Hansen and Baroody (2020)	EHR	X		Pathways to adoption of EHRs
Raman and Grover (2020)	EHR	X		Cohesiveness vs structural holes in effect of adaptation.
Steinhauser et al. (2020)	Tele-health	X		Acceleration of telehealth adoption
Sun et al. (2020)	Tele-health	X		Telehealth reducing emergency room congestion
2022				
Abouzahra and Ghasemaghaei (2022)	Mobile health		X	Wearables and elderly people

Ghose et al. (2022)	Mobile Health		X	Factors increasing use of mobile health platforms
Note: Literature Review based on the AIS scholarly Basket of Eight, consisting of the following journals: European Journal of Information Systems, Information Systems Journal, Information Systems Research, Journal of AIS, Journal of Information Technology, Journal of MIS, Journal of Strategic Information Systems and MIS Quarterly.				

Table 1. Existing Literature on IS Use in Healthcare

This development can also be observed in major IS literature. Prior adaptations in the healthcare context have mainly focused on EHR systems use, while other IS use has received less attention and has only begun to be researched within the last five years (see Table 1). EHR systems alone cannot respond to the needed changes and improvement of healthcare provision. The use of existing EHR systems in combination with artificial intelligence (AI), especially AI-based chatbots, on the other hand, could bring about the desired relief of the health workforce (McKinsey 2020), for example, by reducing costs and optimizing personnel-intensive processes like diagnosis and medication (Comendador et al. 2015; Müller et al. 2020). Therefore, within this dissertation, we mainly focus on the potential of AI-based chatbots to reduce physicians' workload and free resources for the health workforce.

2.2.1 Research Context: AI-Based Chatbots in Healthcare

IS research (Davenport and Ronanki 2018; Tarafdar et al. 2019a) indicates that three types of AI support different business activities and change existing workflows to various degrees. All three types can be combined within one system, building on each other from automation and decision support to engagement.

AI applied for automation optimizes tasks traditionally undertaken by humans, expediting processes and yielding rapid returns. Robotic process automation is a prevalent technology for automation, used to mechanize digital tasks like updating patient data across various platforms. With textual data, robotic process automation frequently collaborates with diverse text mining methods. For example, rule-based algorithms, natural language processing, or machine learning techniques are commonly employed to extract information from unstructured textual data, such as an anamnesis transcript, capturing patients' medical history. Additional text mining tasks, like document summarization, categorization, or topic modeling, further enhance the streamlined processing of unstructured textual data. Automation represents the least 'intrusive' approach to altering established workflows, as it operates within an existing infrastructure. Its primary aim is to assist human endeavors, leading to a high success rate for automation implementations (Davenport and Ronanki 2018).

AI used for decision support enhances functions typically carried out by machines, such as organizing and interpreting extensive datasets. Decision support draws insights from historically labeled data to predict outcomes based on new, unlabeled data. Prevalent predictive algorithms encompass probabilistic models (e.g., Bayesian or Hidden Markov Models), machine learning algorithms (e.g., random forest or artificial neural networks), or statistical algorithms (e.g., multiple linear regression or logistic regression models). These predictive algorithms can also be coupled with prescriptive algorithms to offer adaptive and optimal decisions. Standard prescriptive algorithms encompass probabilistic models, machine learning algorithms, mathematical programming, evolutionary computation, simulations, and logic-based models. The efficacy of results hinges on data quality. AI for decision support serves as a passive supportive tool, depending on active consultation by humans to acquire necessary input for decision-making. The invasiveness with respect to established workflows is moderate, as decision support depicts its own system but remains integrated within existing workflows and interfaces. Decision-support implementations' success rate is moderate (Davenport and Ronanki 2018; Tarafdar et al. 2019a).

AI for engagement entails creating a personalized virtual entity that proposes decisions and actively interacts with humans. AI uses predefined datasets and algorithms to simulate task delegation without human intervention. For this purpose, AI for engagement features a conversational interface that translates spoken language into textual data. Textual data is then analyzed using text mining methods, particularly natural language processing, and processed through predictive algorithms. AI for engagement uses spoken language through natural language generation, fostering a dialogue between a patient and the AI system. AI for engagement triggers the most invasive changes to existing workflows and has been less frequently utilized in practice, often with a lower success rate. Organizations often blend elements from all three AI types to reap optimal benefits from AI integration, especially when using AI-based chatbots (Davenport and Ronanki 2018).

Early chatbots like ELIZA had only rudimentary abilities to participate in conversations using simple decision trees (Schuetzler et al. 2014). Today's AI-chatbots can be defined as computer programs enabling natural language communication between a human and a computer with the help of AI, including natural language processing, pattern matching, and ontologies (Al-Ramahi and Noteboom 2018; Müller et al. 2019a). Mostly, when individuals think of AI-based chatbots, they have in mind famous examples like Alexa, Siri or Google Assistant that belong to the category of general chatbots and can talk about various common topics (Johannsen et al. 2018). But there are also domain-specific chatbots applied for specific application scenarios in a specific field (Følstad et al. 2021; Johannsen et al. 2018), such as finance (Dole et al. 2015), education (Kerry et al. 2009), e-commerce (Baier et al. 2018), marketing (Reis et al. 2022a), and also healthcare (Comendador et al. 2015; Müller et al. 2019b; Oh et al. 2017). Across all these contexts, literature shows that, if implemented successfully, AI-based chatbots can support or replace time- or cost-intensive human-to-human interactions and increase the efficiency and reliability of services. As such, AI-based chatbots can be an effective answer to skill shortage and the lack of personnel (Johannsen et al. 2018).

There are five potential areas in healthcare where AI-based chatbots could be applied. One such application area involves using AI-based chatbots in medical offices to handle the interviewing tasks typically performed by intake nurses (Schuetzler et al. 2014). Another scenario involves using a "Pharmabot" designed specifically to prescribe and recommend medications for children and provide information about the medicines to parents of the young patients (Comendador et al. 2015). In mental healthcare, AI-based chatbots could combine natural language understanding with emotion recognition, enabling psychiatric counseling (Oh et al. 2017). This approach uses a case-based counseling response model integrated with an ethical judgment model and has been successfully utilized in interventions targeting alcohol consumption habits among young adults. Additionally, chatbots have been used to advise patients on which hospital to visit for a specific disease and to collect patient data over time, functioning as a disease diary (Laranjo et al. 2018). These diverse application areas demonstrate the potential of AI-based chatbots to enhance various aspects of healthcare delivery and show that AI-based chatbots could be beneficial in reducing physicians' workload and streamlining processes related to diagnosis, treatment, and medication (Laumer et al. 2019; Müller et al. 2020).

Still, the actual implementation of AI-based chatbots in this context is relatively uncommon (Laranjo et al. 2018), possibly due to the unique characteristics of the healthcare sector. A significant concern is the high sensitivity of patient data (Jena 2015), and the potential for substantial regret (Mattke et al. 2018a), if an AI-based chatbot provides incorrect or misleading information. The consequences of such errors can be far-reaching, as they may lead to wrong medication or incomplete information about a patient's prior treatments, directly impacting people's health and, in the worst-case scenario, posing a threat to their lives (Müller et al. 2019b). Therefore, to realize a successful implementation of AI-based chatbots, we need to respect these specifics of the healthcare sector. This includes carefully considering sensible use cases only and understanding possible perceptions and behaviors related to a potential implementation of AI-based chatbots, including the patients' and physicians’ perspectives. We will outline the theoretical foundation for such considerations hereafter.

2.2.2 Theoretical Foundation: Relevant Behaviors Related to the Implementation of AI-Based Chatbots in Healthcare

The aim of using AI-based chatbots in healthcare is to relieve the health workforce and replace time- and cost-intensive processes. Reaching that aim and successfully implementing AI-based chatbots in healthcare requires their adoption from patients and physicians. Theoretically, when confronted with new IS, depending on the related perceptions, the current non-users can either respond with adoption, turning them into users of the new IS or they resist using the new IS and reject it (Cenfetelli 2004; Maier et al. 2022). In the past, physicians have often refused to adopt new IS despite recognizing their clear benefits concerning task performance and outcome, including, for example, the time and accuracy of computerized medical image interpretation (Longoni, Bonezzi, & Morewedge, 2019). Resistance to change has been identified as a primary barrier to implementation (Bhattacherjee & Hikmet, 2007). The same applies to patients. To realize the benefits of using AI-based chatbots in healthcare, patients must be willing to share their data with them, which a significant portion is not (PricewaterhouseCoopers 2020). According to recent reports, 61 percent of patients do not want to engage with an AI-based chatbot due to the uncertainty about the potentially negative consequences that might come with the AI integration (PricewaterhouseCoopers 2020). Although most patients see the benefits of using AI-based chatbots, such as quicker and easier access to healthcare, faster diagnoses, and better data availability and analysis, they still prefer to stick with their status quo and resist using AI-based chatbots (Deloitte 2019). We, therefore, know that there are potentially severe barriers to patients and physicians adopting AI-based chatbots despite their potential value. Thus, we need to understand the reasons for a potential adoption on the physicians' side and the underlying reasons for the described adverse behaviors opposing an adoption from both physicians and patients, which prior research has labeled as resistance behavior (Lapointe and Rivard 2005).

2.2.2.1 Resistance to AI-Based Chatbots

Individuals' resistance toward a new IS has been an established research stream in both IS and psychology research. This research covers various dimensions of resistance, including behavioral, affective, cognitive, and dispositional aspects (Kim and Kankanhalli 2009; Laumer et al. 2016; Polites and Karahanna 2012). While physicians' reasons for resisting using AI-based chatbots have not been examined so far, patients show resistance behavior due to an unwillingness to change from their current situation to an uncertain new situation with the AI-based chatbot (Deloitte 2019). This observed resistance primarily refers to the behavioral dimension of resistance (Kim and Kankanhalli 2009), defining resistance as the negative behavioral response associated with change. To explain individuals' unwillingness to change, IS scholars (Kim and Kankanhalli 2009; Lee and Joshi 2017; Mattke et al. 2018a; Polites et al. 2017; Polites and Karahanna 2012) and related research (Fernandez and Rodrik 1991; Fleming et al. 2010; Kahneman et al. 1991) have widely referred to the status quo bias perspective (Samuelson and Zeckhauser 1988), considering the costs or threats associated with a change to a new situation.

Status Quo Bias Perspective. The foundation of the status quo bias perspective rests on the assumption that individual decision-making exhibits a bias to maintain the status quo (Samuelson and Zeckhauser 1988). Individuals' choice to resist altering the status quo for an uncertain alternative is not solely rooted in (1) rational decision-making, characterized by a cost-benefit analysis, but is also influenced by biases arising from (2) cognitive and (3) psychological factors that impinge on the rationality of decision-making (Lee and Joshi 2017). Against this backdrop, the status quo bias perspective proposes six variables that align with these three primary categories and collectively contribute to a status quo bias (Samuelson and Zeckhauser 1988).

Firstly, status quo bias can be explained through rational decision-making, wherein favoring the status quo aligns with rationality within a cost-benefit analysis, expressed through transition and uncertainty costs (Lee and Joshi 2017). Transition costs make any departure from the status quo burdensome and contribute to status quo bias if the costs of switching outweigh the gains from change (Samuelson and Zeckhauser 1988). Uncertainty costs involve investing time and resources to evaluate alternatives to the status quo amidst uncertainty, such as potential outcomes. The low probability of failure associated with the status quo contributes to the status quo bias.

Secondly, the status quo bias emerges when the assessment of an alternative state is biased by cognitive misperceptions favoring the current state. Loss aversion plays a pivotal role in this cognitive distortion, as potential losses tied to the status quo outweigh potential gains, swaying assessments in favor of maintaining the current state (Samuelson and Zeckhauser 1988).

Thirdly, psychological commitment contributes to the status quo bias. Individuals tend to validate their situation in subsequent decisions to affirm their decision-making accuracy and maintain control. This commitment is influenced by factors like sunk costs, anticipated regret, and decisional control (Samuelson and Zeckhauser 1988). Sunk costs signify investing time and resources to establish the status quo, whereas more significant investments intensify the desire to preserve it. Anticipated regret refers to individuals' efforts to evade potential threats or consequences, allowing them to avoid the future feeling of making an erroneous decision (Liang and Xue 2009). Furthermore, maintaining the status quo can stem from the desire to exert decisional control. Actively deciding favoring the status quo gives the illusion of better control (Samuelson and Zeckhauser 1988). Overall, the status quo bias perspective is based on the tenet that individuals' decision-making is biased in favor of the status quo when individuals resist changing the status quo for an uncertain alternative state, explaining resistance in response to uncertainty. As such, we consider it suitable to examine patients' resistance to using AI-based chatbots.

2.2.2.2 Adoption of AI-Based Chatbots

So far, previous research has not explicitly developed theories about adopting AI-based chatbots. Nonetheless, recent observations in the literature examining meaningful applications of AI in healthcare (Müller et al. 2019b) and other industries (Davenport and Ronanki 2018; Rai 2020) suggest that physicians' adoption of AI, particularly of AI-based chatbots, is influenced by three key characteristics. The invasiveness, the complexity and the consequences of AI adoption. When the level of invasiveness is high due to insufficient support systems, it necessitates the simultaneous consideration of perceptions regarding both the IS and AI-specific aspects. Conversely, if the invasiveness level is low, only AI-specific perceptions require assessment, as familiarity with the integrated system already exists (Tarafdar et al. 2019a). Higher complexity leads to interconnected perceptions concerning physicians, patients, and potential consequences, requiring a combined approach. In contrast, lower complexity allows for separate assessment of these perceptions (Davenport and Ronanki 2018). Further, the potential for far-reaching AI-related consequences influences the evaluation process (Rai 2020). If this potential is substantial, it prompts trade-off of consequences and yielding factors involved in the adoption decision. Conversely, this assessment is unnecessary if the potential for far reaching consequences is limited. In cases where the AI adoption's invasiveness, complexity, and potential for far-reaching consequences are high, the adoption decision becomes intricate and a separate processing of perceptions is unfeasible (Furnari et al. 2020). Therefore, while IS adoptions with lower values for these characteristics might be compatible with existing theories of IS adoption (e.g., Davis 1989; Venkatesh et al. 2003), higher degrees of these characteristics constrain the applicability of these theories.

2.2.3 Related Research and Research Opportunities

Based on the described research context of AI-based chatbots in healthcare and the theoretical foundation of implementation-related use behaviors, we present related research in that field and deduce specific research opportunities.

2.2.3.1 Related Research and Research Opportunities: Sensible Use Cases for AI-Based Chatbots in Healthcare

To make IS use part of the solution to health system overload, we must successfully implement AI-based chatbots that reduce costs and free health workforce resources. A successful implementation starts with sensible use cases (Irwin and Turk 2005) for AI-based chatbots in healthcare. The literature outlines five distinct usage scenarios for chatbots in healthcare, rated as sensible from the patients' standpoint (e.g., Oh et al. 2017). These scenarios encompass diagnosis and patient interviews, medication guidance, psychiatric counseling, hospital advice, and maintaining a disease diary. Despite these instances, there remains a constrained understanding of sensible application situations and the subsequent opportunities for enhancing processes for both healthcare providers and patients. Previous research has uncovered only restricted and highly particular use cases with limited applicability across various contexts, and none have incorporated the perspective of healthcare professionals. Therefore, **Paper VI** aims to capture the physicians' perspective on sensible use cases of AI-based chatbots in healthcare to uncover those areas with the highest potential to reduce physicians' workload.

2.2.3.2 Related Research and Research Opportunities: Adoption and Resistance to AI-Based Chatbots in Healthcare

After identifying sensible use cases, we aim to examine implementation-related user behaviors, namely resistance toward and adoption of AI-based chatbots in healthcare, to uncover critical aspects of a successful implementation.

Resistance to AI-Based Chatbots in Healthcare. Although using AI-based chatbots provides clear benefits, physicians and patients still show resistance and prefer to stick with their status quo (Deloitte 2019). Prior research on AI-based chatbots in healthcare has only considered positive user reactions to the described use cases (Denecke et al., 2018), leaving the observed patient and physician resistance untouched (PricewaterhouseCoopers, 2020). While lots of research in the stream of resistance to IS in healthcare has tackled the topic of resistance and offers valuable insights, the results do not respect the specific context of using AI-based chatbots but electronic health records (Bhattacherjee and Hikmet 2007; Doolin 2004; Kane and Labianca 2011; Murungi et al. 2019; Nov and Schecter 2012). Further, only limited insights exist on the effects of status quo bias in healthcare (Hsieh 2015), and none treating status quo bias in response to AI-based chatbots and the specifics of this use context. Among others, the communication abilities of AI-based chatbots differ from more 'traditional' IS in healthcare and may raise specific worries regarding direct interaction with the patient, which needs to be considered when studying resistance. Further, those studies on IS use in healthcare foremost consider the physicians' perspective. Patients represent the demand side of healthcare with motivations, aims, and perceptions different from the supply side (Penman et al., 1984). Therefore, **Paper VII** examines the reasons for patients' resistance, and **Paper IX** tackles physicians' resistance in the specific context of AI-based chatbots, which remains understudied so far.

Adoption of AI-Based Chatbots in Healthcare. Current IS adoption theories (e.g., Davis 1989; Venkatesh et al. 2003) predominantly encompass pertinent IS perceptions like ease of use, perceived usefulness, and social attributes like image. These theories do not contain AI-specific perceptions, including the ability to engage in human-like interactions (Rzepka and Berger 2018) and interpret data (Rai 2020). The absence of these aspects limits our understanding of perceptions that go beyond established IS adoption concepts. Moreover, from a theoretical standpoint, the interconnected nature of perceptions tied to AI-based chatbots that influence adoption decisions, alongside evaluating predominant potential consequences, surpasses the explanatory power of current theories. Thus far, existing IS perception theories posit independent and separate impacts on individuals' adoption intentions (Furnari et al. 2020; Sussman and Siegal 2003). In that respect, **Paper VIII** of this dissertation suggests an alternative approach for examining the processing of perceptions forming the intention to adopt AI, respecting interdependent perceptions and their potential to yield consequences for physicians and patients, as well as the prioritization of these potentials in forming the intention to adopt AI. Existing research offers the concept of enablers and inhibitors, defined as perceptions attributed with a specific potential to influence the intention to adopt, respecting the resulting consequences (Cenfetelli 2004). These enablers and inhibitors can be present or absent. Present enablers are attributed with the potential to foster the intention to adopt, and absent enablers have the potential to hinder the intention to adopt. Present inhibitors are attributed with the potential to hinder the intention to adopt, whereby the potential of absent inhibitors does not have an influence (Cenfetelli and Schwarz 2011). To examine physicians' processing of enablers and inhibitors related to AI-based chatbots, respecting the interdependence of enablers and inhibitors and the prioritization of the potentials in forming the intention to adopt requires new approaches to adoption based on complex decision-making (Campbell et al. 2016), which we aim to offer in this dissertation.

2.4 Summary

According to the logic of double effects (Monge and Hsieh 2020), recommending IS use as a remedy for health system overload is only morally acceptable if we can minimize the unintended burdening effects and if the supporting effects outweigh the burden. Overall, the literature shows the dual nature of IS use in health system overload and reveals some research opportunities to work on (see Table 2 for a summary).

<table>
<tr><td rowspan="7">Chapter 1</td><td colspan="2">Goal 1: Understand how IS use, specifically social media, mobile apps, and remote working tools, causes burdening effects on mental health and how to prevent them.</td></tr>
<tr><td>Paper</td><td>Research opportunities</td></tr>
<tr><td>Paper I</td><td>Stress potential of influencer marketing, specifically yielding social comparison</td></tr>
<tr><td>Paper II</td><td>Stress potential of in-app advertising and related coping reactions</td></tr>
<tr><td>Paper III</td><td>Underlying motivations of ad-blocker usage as a problem-focused coping approach</td></tr>
<tr><td>Paper IV</td><td>Conceptualization of remote work stress and related mitigations</td></tr>
<tr><td>Paper V</td><td>Technostress of IT professionals and specific mitigations in the work context</td></tr>
<tr><td rowspan="6">Chapter 2</td><td colspan="2">Goal 2: Identify pathways to successfully implementing AI-based chatbots in hospitals.</td></tr>
<tr><td>Paper</td><td>Research opportunities</td></tr>
<tr><td>Paper VI</td><td>Sensible use cases with potential for physicians and patients</td></tr>
<tr><td>Paper VII</td><td>Status quo bias and aspects of patient resistance</td></tr>
<tr><td>Paper VIII</td><td>Physicians’ adoption of AI-based chatbots</td></tr>
<tr><td>Paper IX</td><td>Physicians’ resistance towards AI-based chatbots and pathways to a successful implementation</td></tr>
</table>

Table 2. Summary of Theoretical Research Opportunities

Concerning the minimization of burdening effects, literature shows that the intensified use of IS entails the risks of burdening individuals’ mental health through negative emotions and technostress, which has been recently considered increasingly in existing IS research, but foremost in the work context (Fischer and Riedl 2017). The considerations have not included the stress potential of IS-enabled advertising, received via social media and mobile apps, of remote work or specific mitigations in these fields. Concerning the supporting effects, the literature has stressed the benefits of implementing AI-based chatbots in healthcare. Still, it does not sufficiently reveal sensible use cases or factors influencing implementation-relevant behaviors, such as resistance or adoption, that could yield implementation and the associated benefits as a counterpoint to the potential burden (see Figure 3).

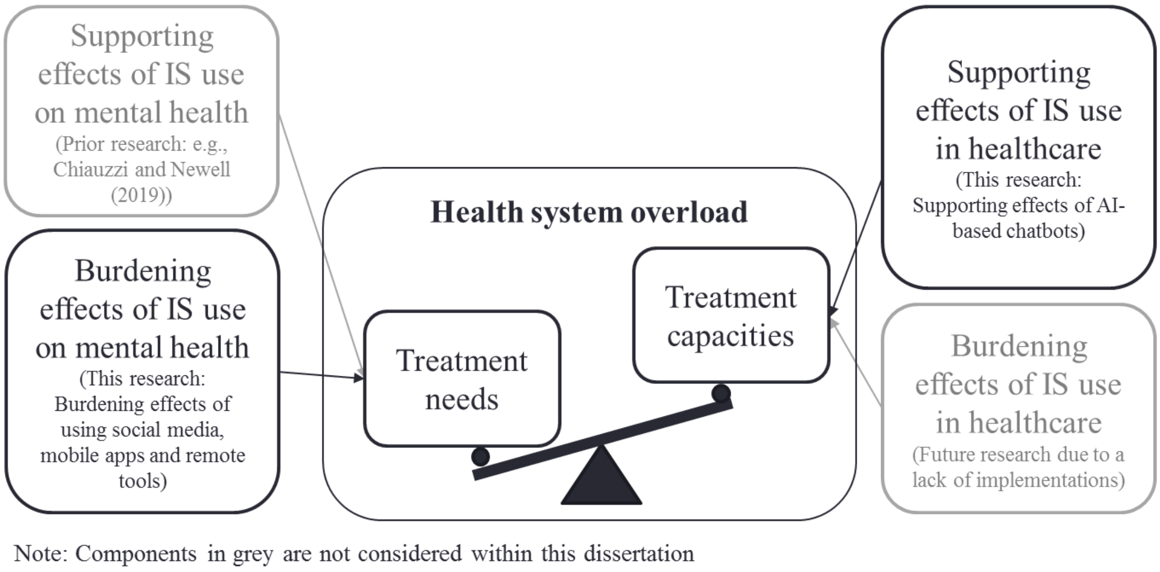

Figure 3. The Role of IS Use in Health System Overload, as Examined in this Dissertation

This dissertation wants to take advantage of these opportunities and applies a methodological pluralism to tackle them. We present the details of our methodological approaches next.

3 METHODOLOGY

This dissertation includes several research methods, such as literature reviews, qualitative interviews, quantitative surveys, configurational studies, and mixed-methods approaches to address the identified research opportunities. This methodological pluralism allows us to leverage each method's strengths and deliver holistic and generalizable results. The following sections explain the used methodologies and identify possibilities to contribute methodologically to IS research.

3.1 Literature Review

All twelve research papers and the introductory paper draw from a solid knowledge base extracted from current literature. Scholars advise using literature reviews to identify and structure this knowledge (Paré et al. 2015). Literature reviews apply structured search approaches that allow for identifying, analyzing, and presenting relevant literature from a relevant search scope. For this dissertation, we consider the *AIS Senior Scholars' Basket of Eight* a representative source of IS literature, following recommendations in existing research (Moeini et al. 2019). The AIS Senior Scholar's Basket of Eight consists of the following journals: European Journal of Information Systems, Information Systems Journal, Information Systems Research, Journal of AIS, Journal of Information Technology, Journal of MIS, Journal of Strategic Information Systems, and MIS Quarterly. We enlarged this scope to relevant marketing or health journals, where applicable. Further, following examples in prior research (Chipidza and Leidner 2019), we consulted established guidelines on how to conduct a structured literature review, using techniques borrowed from grounded theory research for "rigorously reviewing literature" (Wolfswinkel et al. 2013), that consist of five steps: Define, search, select, analyze, and present.

In the define phase, we set the scope of the review and gather relevant keywords to conceptualize the topic (vom Brocke et al. 2009; Wolfswinkel et al. 2013). Then, we search for our keywords in the relevant databases, select relevant articles based on exclusion criteria, and perform forward and backward searches based on the gathered articles (Webster and Watson 2002). After reading and analyzing the literature, we present the results in a concept matrix and deduce opportunities for future research (vom Brocke et al. 2009; Wolfswinkel et al. 2013).

Paper X provides a structured literature review following this scheme to identify IS literature using mixed-methods approaches after the publication of the guideline paper by Venkatesh et al. (2013). We searched the Basket and identified 111 articles, which we narrowed to 57 papers to analyze. Leveraging the insights of those papers enabled us to deduce condensed and applicable guidelines for mixed-methods research, which prior research has not provided up to this point (Walsh 2015).

3.2 Qualitative Approaches

Qualitative approaches enable us to examine phenomena that require inductive research to detect new concepts or relationships (Yin 2018). They present subjective views on the same phenomena, answering “what”- and “why”-questions and allowing for a constructivist reality. As such, qualitative methods acknowledge the existence of multiple realities shaped by the subjective perceptions and pre-experience of the participant and the researcher that together describe reality (Mingers et al. 2013).

Within this dissertation, we primarily use semi-structured interviews as qualitative research approaches, either as a stand-alone method (**Papers V, VI, and IX**) or as part of our mixed-methods approaches (**Papers II, III, IV, VII, and XI**), which we will outline later. Following examples in the literature (Myers 2019; Myers and Newman 2007), we divide our qualitative approaches into a description of the data collection, analysis, and validation.

In the data collection phase, we first set up an appropriate semi-structured interview guideline (Myers and Newman 2007) that always consisted of an introduction part, where we introduce ourselves and the project, the interviewees presented themselves, and we gained informed consent for the recording and anonymous analyzing of the interviews. Then, we asked specific questions about the main topic and closed with some open questions to end the interviews. After the set-up of the guideline, we select an appropriate data sampling strategy that consisted of selecting the right interviewees and identification methods of these interviewees (Collins et al. 2006). The demographics of the final sample are presented in the papers along with a description of the interview setting, which was face-to-face in our laboratories or via digital technologies due to the pandemic. Concerning the data analysis, we followed established guidelines (Kuckartz 2016; Myers 2019) that combine deductive and inductive coding approaches to analyze and categorize the given answers. We present those codes in a representative coding scheme. In the data validation phase, we ensured the independence of the coding approach by involving several independent coders, checking for inter-coder reliability, and checking our results with the interviewees to get interpretative validity (Feng 2014; O’Connor and Joffe 2020).

In **Paper V**, we conducted semi-structured interviews with 30 white-collar workers, specifically 23 specialists, five managers, and two CIOs working in the IT departments of two medium-sized organizations in the production industry, one in fashion and one in systems engineering.

Those interviews helped us to understand the role of technostress and specific mitigations. In **Paper VI**, we asked 23 physicians from different departments about applying AI-based chatbots in their field to get an idea of sensible use cases for physicians and patients. With **Paper IX**, we initially followed an implementation project of an AI-based chatbot passively. Then, we participated in the project to investigate the reasons for the failure and to understand why physicians resisted and ultimately rejected this AI implementation. To this end, we interviewed 16 physicians on-site in the hospital.

3.3 Quantitative Approaches

Quantitative approaches allow the confirmation of formerly deduced hypotheses and answer questions of "how", concerning the relationships and effects among certain constructs (Teddlie and Tashakkori 2008). They embrace a positivist worldview, which focuses on approximating reality that can be measured and proved, independent of subjective interpretations (Mingers et al. 2013). Within this dissertation, we base our quantitative approaches on quantitative survey data collected through online questionnaires and analyzed with structural equation modeling (SEM), as presented in **Paper I** and as part of our mixed-methods approaches described later (**Paper VI and XII**). We outline our approach in more detail hereafter.

3.3.1 Quantitative Data Collection with Questionnaires

Questionnaires are an appropriate tool to collect large amounts of primary data that reflects a specific target group's characteristics, opinions, perceptions, or attitudes (Chen and Hirschheim 2004). Providing the base for the data collection, the questionnaire needed to be designed carefully to ensure high-quality data. Among others, the questions needed to be consistent and free of any influence. Self-completion questionnaires, especially when shared via crowdworking platforms, impose further constraints on high data quality and require, among others, the monitoring of response time, response patterns, or screening questions that require certain answers to continue (Lowry et al. 2016). Further, when designing the measures for certain constructs, to ensure content validity, integrated items used in prior research (Straub and Gefen 2004) or relied on Q-sorting (Nahm et al. 2002; Stephenson 1953) to validate the used items. Q-sorting consists of a task where items need to be associated with constructs. The sorting needs to surpass the threshold of 0.61 to count as reliable. In line with prior research (Podsakoff et al. 2003), we also recognized that self-reported data could impose common method bias (CMB). Besides strong correlations between bivariate correlations ($r > 0.90$) giving a first hint at CMB (Pavlou et al. 2007), there are two statistical analyses to identify the extent of CMB. First, Harman's single-factor test indicates whether the majority of the variance can be explained by one single factor, which needs to be below the 50 percent-threshold (Podsakoff et al. 2003). Second, a CMB-factor can be added to the statistical analysis (Podsakoff et al. 2003; Williams et al. 2003) that contains every indicator of the original model. The remaining original factors are then transformed into single-item constructs. Next, we compared the ratio of the coefficient of determination (R2) with the CMB-factor to R2 without the CMB-factor and deduced the extend of CMB from there (Lindell and Whitney 2001). We used a 7-Likert-scale with seven depicting "strongly agree" and one "strongly disagree." All papers provide detailed descriptions of the circumstances of the data collection, sampling strategy, extent of common method bias and characteristics of the target group.

3.3.2 Quantitative Data Analysis with Structural Equitation Modeling

Structural equitation modeling (SEM) enables us to test formerly deduced hypotheses empirically. Combining different aspects of regression and factor analysis, SEM allows the simultaneous examination of models with multiple dependent variables and their interconnections (Gefen et al. 2011). A proper SEM analysis consists of the measurement model and the structural model. The measurement model specifies the direction of the relationship between variables and indicators, and the structural model defines relationships in terms of hypothesized causal dependencies between variables (Ringle et al. 2012).

Validation of the Quantitative Measurement Model. Besides content validity, assuring that the measurement instrument is representative of the respective construct through the selection of pre-validated items (Nahm et al. 2002; Straub and Gefen 2004) and a measurement of the extent of CMB explained above (Lindell and Whitney 2001; Pavlou et al. 2007; Podsakoff et al. 2003), there are more validity criteria to consider. The measurement model has to account for discriminant validity, referring to constructs sufficiently differing from each other (Henseler et al. 2014). Therefore, we need to check two values. First, the square root of the average variance extracted (AVE) needs to exceed the corresponding bivariate correlations of the respective construct (Fornell and Larcker 1981), and second, the heterotrait-monotrait (HTMT) ratio must be below the threshold of 0.85 (Henseler et al. 2014). Further, the measurement model has to prove convergent validity testing for how much a measure correlates with alternative measures within the same construct on either the item or the construct level (Hair et al. 2017). At the item level, the loading should exceed 0.707, indicating an explanatory power of the item of at least 50 percent (Carmines and Zeller 2008; Hair et al. 2017). At the construct level, the AVE should surpass the value of 0.50 (Fornell and Larcker 1981). Lastly, we need to ensure construct reliability, depicting the internal consistency of a construct.

Cronbach's alpha (α) and the composite reliability (CR) exceeding 0.70 each indicate a high construct reliability (Hair et al. 2017; Nunnally 1978).

Analysis of the Structural Model. The effectiveness of the structural model can be assessed through two key metrics: the coefficient of determination (R^2) and the significance level of each path coefficient (Chin 1998). R^2 represents the proportion of variance in the data that the statistical model can account for, and it should be relatively high to explain the variance of the dependent variables effectively. R^2 values of 67%, 33%, and 19% are categorized as substantial, moderate, and weak, respectively (Chin 1998). The path coefficients, akin to standardized beta coefficients obtained from ordinary least squares regressions, offer insights into the relationships within the model. Researchers often employ the bootstrapping technique to determine the significance of these path coefficients and identify the level of significance. This method helps ascertain whether a path coefficient holds statistical significance and at what significance level it operates ($p<0.001$: highly significant, $p<0.01$: significant, $p<0.05$ weakly significant). Throughout this dissertation, we used partial least squares (PLS) path modeling to perform the SEM analysis with the help of the software application SmartPLS3 (Ringle et al. 2015).

In **Paper I**, we used a quantitative study based on survey data to validate our research model on the negative effects of influencer marketing empirically. We prepared an online survey and shared it via social media, which matched our sampling strategy to get a non-probability sampling of social media users. We applied all the validity and quality checks to ensure high data quality and excluded datasets from our 191 responses. The final sample consists of 152 data sets. As outlined above, we analyzed the measurement and structural models with the help of SmartPLS3 (Ringle et al. 2015).

3.4 Configurational Approaches

Configurational approaches, such as qualitative comparative analysis (QCA) that we used in this dissertation, let us cast light on the multidimensional interplay between influencing factors (El Sawy et al. 2010; Park et al. 2020). To this end, QCA draws on set theory and uses Boolean algebra to explain the relationship between multiple causal conditions, or configurations of those causal conditions, and the examined outcome (Mattke et al. 2022; Ragin 2014). Specifically, QCA identifies relationships of necessity and sufficiency (Schneider and Wagemann 2012). A necessary condition refers to a causal condition that always exists when the outcome condition exists, and a sufficient condition always leads to the examined outcome (Ragin 2014). Initially developed to explain complex social science phenomena (Ragin 2014), QCA has been increasingly used in IS research lately to describe relationships far more complex than linear relationships, which helps to avoid oversimplification or incomplete interpretation of IS-related research phenomena (Mattke et al. 2021b). This development can be mainly attributed to QCA's power to investigate three specific aspects of causal complexity (Misangyi et al. 2017): Firstly, QCA can discern causal asymmetry in relation to both the presence and absence of individuals' behavior. This analysis reveals distinct sets of sufficient conditions for explaining when individuals' behavior is present or absent (Fiss 2011). It is important to note that these sufficient conditions for presence and absence can exhibit asymmetry, meaning that the configurations explaining the presence of individuals' behavior can differ significantly from those explaining its absence. Secondly, QCA respects equifinality, which signifies that the examined outcome can be reached through multiple distinct sufficient configurations (Mattke et al. 2022). In essence, QCA not only provides a single, solitary explanation for individuals' behavior but multiple potential explanations expressed thorough multiple configurations. Thirdly, QCA can detect asymmetric relationships between causal conditions. This implies that various combinations of high and low levels of causal conditions, combined into one or more configurations, can be linked to individuals' behavior (Woodside 2017). Consequently, a specific causal condition's high or low level may or may not be related to individuals' behavior, depending on the simultaneous existence of and interaction with other causal conditions within a given configuration (Mattke et al. 2022). As such, the same causal condition can have different implications for individuals' behavior based on the specific pattern of other causal conditions within the configuration.

Within this dissertation, we used QCA as a stand-alone method in **Paper VII** and in combination with other methods in a mixed-methods design in **Papers II, III, VIII, XI, and XII**. Following the guidelines (Mattke et al. 2022), we used a seven-step framework to conduct our QCA studies.

In the first step, we develop a configurational research model, justifying configurational methods with a theoretical foundation of factors' intertwined, configurational relations. In the second step, we collected data with the help of quantitative survey questionnaires. This step showed many parallels to our quantitative approach, as the design of the questionnaire and the tests for validity (content and discriminant validity), reliability, and common method bias remained the same as described above. Specifically for the QCA approach, we needed to sample configurations leading to a high and a low level of the outcome and reach a minimum proportion of conditions to observations, so datasets, of 0.20 (Mattke et al. 2022). In the third step, the calibration, we needed to convert the interval-scaled variables of a research model into fuzzy sets. We used direct calibration by using three different anchors: the anchor for full-non-membership in the set, crossover point, and full membership in the set. For variables measured on a 7-Likert-scale, using the values 1, 4 and 7 as anchors is common. Other variables, such as gender, could be transformed into crisp-sets only having two values.

In the fourth step, the analysis for necessary conditions, we tested whether the presence of a single condition or the absence of a single condition was necessary for the outcome, thus exceeding the consistency threshold of 0.90, the coverage threshold, and the relevance of necessity threshold of 0.60. In step five, we first needed to construct the truth table based on the calibrated data to examine, which sufficient configurations lead to a high outcome. This means that we listed all existing configurations, examining which of them was sufficient for a high outcome and then determined a consistency threshold (needs to exceed 0.85), a proportional reduction in inconsistency (PRI) threshold (needs to exceed 0.75), and a frequency threshold (needs to be higher than three). The frequency threshold reduced the truth table to configurations found at least three times. The consistency threshold then determined whether a configuration (with at least three observations) was sufficient for the outcome. The PRI thresholds reduced the truth table to configurations that were only sufficient for the presence of the outcome but not for the absence. In summary, this step resulted in a reduced truth table containing configurations with at least three observations determined as sufficient for the outcome. After that, we applied the Quine-McCluskey algorithm to simplify the configurations, which produced the solution (in terms of the intermediate solution). Additionally, the algorithms produced a complex solution and a parsimonious solution. Based on them, we specified core conditions. Core conditions are conditions that appear in the parsimonious and the intermediate solution. The same procedure was then applied to sufficient configurations for a low outcome, where applicable.

In step six, we graphically reported the minimized sufficient configurations, including the necessary conditions (see Figure 4 for an example). In this graphical representation, present conditions are indicated with ●, absent conditions are indicated with ⊗), or either present or absent conditions, which refer to a 'don't care situation' (in the results indicated with blank space). The graphical representation also shows relevant coverage and consistency values on the configuration and solution level to ensure the robustness of the model. These values included the raw coverage for the configuration level, quantifying the portion of the data set explained by one configuration, the unique coverage, presenting the explanatory power of one configuration without the other equifinal solutions, and the consistency indicating the reliability of the configuration exhibiting the outcome. On the solution level, we needed to report the solution coverage, indicating the extent to which the observations in the data set fit at least one configuration of the solution and the solution consistency quantifying the portion of observations in the dataset corresponding to the solution.

	High		Low	
	Example configuration 1	Example configuration 2	Example configuration 3	Example configuration 4
Example condition 1	●	⊗	☆	☆
Example condition 2	★	★	●	⊗
Example condition 3	●		●	●
Raw coverage				
Unique coverage	0.93	0.96	0.77	0.75
Consistency	0.91	0.77	0.99	0.92
Solution coverage	0.77			
Solution consistency	0.93			

Note: Black circles (●) show high motivation, white crossed-out circles (⊗) show low motivation, and blank spaces ( ) indicate a 'Don't care situation.' In this case, the specific condition is irrelevant to the configuration and can either be high or low. Black stars indicate a present necessary condition, white stars an absent necessary condition..

Figure 4. Example Graphical Representation of QCA Results

Lastly, in step seven, we checked for the robustness of the solution and calibration to method decisions (Maggetti and Levi-Faur 2013). Concerning the robustness to changes in thresholds, it is worth noting that QCA can undergo significant alterations leading to the including or excluding of a sufficient configuration. Such variations may occur when adjusting the frequency, raw consistency, or PRI consistency thresholds. Therefore, it is advisable to document the threshold ranges within which the solution remains stable. When presenting the complete truth table, the model's robustness concerning changes in the frequency, raw consistency, and PRI consistency thresholds becomes evident. In the case of the reduced truth table, it does not provide any insights into observations that fall just below the frequency threshold. Consequently, it is recommended to expand the reduced truth table to encompass observations nearest to the frequency threshold. Alternatively, we can replicate the analysis with a lower frequency threshold and report whether the results are substantially altered. Concerning the robustness to changes in calibration, we needed to consider that QCA results can also exhibit sensitivity to the chosen calibration anchors, especially when dealing with non-standardized data and non-uniform calibration thresholds. Therefore, it is prudent for researchers to duplicate their analysis using different calibration anchors in such cases. Furthermore, when making small adjustments, such as adding a minor constant to fuzzy values at 0.50, it is advisable to conduct a corresponding analysis by subtracting a small constant and vice versa.

In **Paper VII**, we used QCA to examine the interplay of factors during a contextualization (Hong et al. 2014) of the status quo bias perspective to patient resistance to AI-based chatbots. We sampled 175 patients who have consulted a physician at least ones within the period of one year. After ensuring data quality regarding the validity, reliability, and common method bias, we conducted two fuzzy-set QCA approaches on the same sample with the QCA R package (Duşa 2018) and the fsQCA 3.0 software (Ragin et al. 2016). We identified four sufficient configurations each. Observing the changes between both QCA analyses enabled us to see the contextualization-induced changes of the model on the interaction level.

3.5 Mixed-Methods Approaches

Mixed-methods approaches offer the opportunity to investigate both exploratory and confirmatory questions in the IS research field within a single research inquiry (Venkatesh et al. 2013). In contrast to multimethod approaches, combining methods from the same research paradigm (Mingers 2001), integrating methodological approaches from two different research paradigms within a single study, mixed-methods approaches present two critical advantages. Firstly, mixed-methods studies yield robust inferences and comprehensive insights into a specific phenomenon. These insights are derived by harnessing the complementary strengths and distinct weaknesses of different methods and go beyond the insights of employing either method in isolation (Nunamaker et al. 2017). Secondly, mixed-methods research allows for incorporating various epistemological perspectives and paradigmatic assumptions in research approaches. This flexibility enables researchers to draw diverse and, at times, conflicting findings from both explorative and confirmatory analyses. Consequently, this combination strengthens the robustness of the theoretical assumptions derived from both studies, often called meta-inferences (Teddlie and Tashakkori 2008). Drawing from the paradigms of pragmatism or critical relativism, mixed-methods approaches provide the capacity to view a single phenomenon from multiple angles and acknowledge the existence of numerous ontological realities (Mingers et al. 2013; Zachariadis et al. 2013). Taking advantage of those benefits, this dissertation used mixed-methods approaches in six papers, either combining qualitative and quantitative research (**Paper IV**), qualitative and configurational research (**Papers II, III, VIII, and XI**), or quantitative and configurational research (**Paper XII**).

To successfully combine paradigms, extant research provides detailed guidelines on design decisions and the structure of mixed-methods studies, especially treating the paradigmatic combination of qualitative and quantitative methods and the deduction of meta-inferences combining both (Venkatesh et al. 2013; Venkatesh et al. 2016). While some works rate those guidelines as the widely adopted standard in IS research (Siponen et al. 2021; Venkatesh et al. 2016), others characterize them as dense and complex, raising doubts about their practicality and proven advantages, and tried to clarify the essentials (Siponen et al. 2021; Verhagen et al. 2015; Walsh 2015; Yu and Khazanchi 2017). Across all these studies, the three core concepts are the purpose of the mixed-methods approach, the meta-inferences, and the validation of inferences.

Purpose. Stating the exact purpose of mixed-methods studies is essential, as it shapes the study design, leading to the derivation of qualitative, quantitative, and meta-inferences (Ågerfalk 2013). Selecting a purpose also helps justify why combining methods is necessary to investigate a particular research phenomenon and how the investigation benefits from different research paradigms. Literature presents seven purposes of mixed-methods studies (Venkatesh et al. 2013; Venkatesh et al. 2016): complementarity, completeness, developmental, expansion, corroboration/confirmation, compensation, and diversity. The complementarity purpose seeks to provide complementary perspectives on the same phenomenon. Completeness aims to offer a comprehensive understanding of a phenomenon from various angles. Research with a developmental purpose involves drawing inferences and validating hypotheses within the same study, contributing to theory development. The expansion purpose allows for exploring inconclusive or unexpected findings, contributing to a deeper understanding. Mixed-methods studies with a corroboration/confirmation purpose strive for robust results by validating one study with another. Compensation aims to address the weaknesses of one method or study design through the strengths of another. Finally, diversity aims to capture different perspectives from varied populations or characteristics. A mixed-methods approach might not be warranted if a proposed study design does not align with the described purposes. In such cases, the contribution of a single study from one research paradigm might suffice (Venkatesh et al. 2016).

Meta-Inferences. Meta-inferences play a pivotal role in mixed-methods research, as they serve as the linchpin that unites inferences drawn from different research paradigms. The absence of identified meta-inferences in a mixed-methods study may suggest that the chosen purpose is not being effectively fulfilled, rendering the study either unnecessary or at the very least, less effective. Meta-inferences are theoretical statements that transcend the paradigmatic boundaries of purely positivist or constructivist research by displaying the added value of combining both research approaches. Consequently, it is imperative to express them clearly (Mingers et al. 2013). To formulate meta-inferences, it is necessary to identify both convergent and dissonant inferences from the combined studies and enhance the individual inferences with complementary or converging knowledge or a blend of both. Due to this integration, meta-inferences extract the knowledge that one study alone could not have yielded, which depicts the true value of mixed-methods approaches (Ågerfalk 2013).

Validation of Inferences. Mixed-methods studies aim to yield robust results that cannot be achieved by one method individually. This is accomplished by leveraging the complementary strengths and distinct weaknesses of methods from different research paradigms. Consequently, a significant aspect of conducting mixed-methods research revolves around validation. Following established guidelines from prior research, each type of inference (qualitative results, quantitative results, meta-inferences) must undergo separate validation. The quality of meta-inferences, and by extension, the quality of the theoretical assumptions derived from the mixed-methods study, hinges decisively on the quality of inferences generated by individual studies. Therefore, it is imperative to ensure the validation of all inferences (Mingers et al. 2013).

Besides agreeing on and describing these three core concepts, prior literature has not yet provided practicable guidelines on how to install them, nor advise on how to integrate configurational approaches (Siponen et al. 2021; Venkatesh et al. 2013; Verhagen et al. 2015; Walsh 2015; Yu and Khazanchi 2017). With **Paper X**, we took advantage of this opportunity and developed condensed guidelines that we also used in the mixed-methods studies of this dissertation, encompassing qualitative, quantitative and configurational methods. Table 3 shows a detailed overview of the papers applying mixed-methods approaches.

Paper	Research approach			Purpose and aim
	Qualitative	**Quantitative**	**Configurational**	
Paper II	26 semi-structured interviews with mobile app users to uncover in-app advertising stressors and coping responses		205 quantitative questionnaires analyzed twice with fuzzy-set QCA showing which configuration of stressors yields which coping responses	Complementary mixed-methods approach, enriching the interviews with configurational knowledge
Paper III	44 semi-structured interviews with current non- to identify related intrinsic and extrinsic motivations and components of amotivation contributing to ad-blocker adoption		249 quantitative questionnaires analyzed with fuzzy-set QCA, uncovering the interplay of these components of motivations as stated in the interviews	Confirmation and developmental approach understanding different components of motivation yielding ad-blocker adoption
Paper IV	22 semi-structured interviews with remote workers capturing remote work stressors, strains, and outcomes	131 quantitative questionnaires analyzed with SEM to identify the influence of certain stressors on the identified strains and outcomes		Developmental approach proposing a remote work stress model and empirically validating it
Paper VIII	16 semi-structured interviews compensate and expand the findings of our QCA study to illustrate the causation phase of decision-making		154 quantitative questionnaires of physicians analyzed with fuzzy-set QCA illustrating the decomposition and integration phase of decision-making	Compensation and expansion approach theorizing and validating physicians' adoption decision of AI-based chatbots
Paper XI	73 semi-structured interviews with current non-investors capturing perceptions and motivations behind bitcoin investment		150 quantitative questionnaires analyzed with fuzzy-set QCA showing configurations of motivations yielding bitcoin investment	Developmental approach to develop and empirically validate a theoretical model for bitcoin investment
Paper XII		178 quantitative questionnaires analyzed with SEM to capture the influence of challenge and hindrance stressors on IS Use	QCA analysis of the same data set to investigate inconclusive findings of the SEM analysis	Expansion approach to clarify the influence of challenge and hindrance stressors on routine and innovative IS use

Table 3. Overview of Mixed-Methods Approaches Used in this Dissertation

3.6 Summary

To uncover the burdening and supporting effects of IS use on health system overload, this dissertation applied several research methods, such as literature reviews, qualitative interviews, quantitative surveys, configurational studies, and mixed-methods approaches to provide high-quality results (please see Figure 5 for an overview).

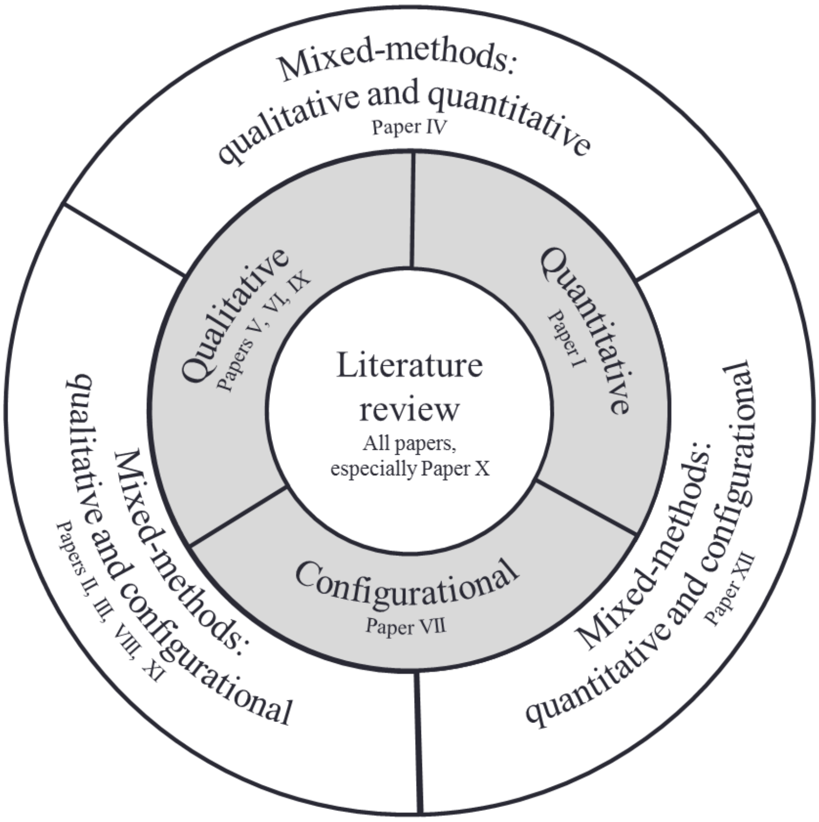

Figure 5. Overview of Methodologies

From applying and leveraging theoretical knowledge about mixed-methods approaches, we realized that there have been various, so far unsuccessful attempts to more practicable guidelines for conducting mixed-methods research. We want to follow this opportunity (see Table 4) in **Chapter 3** with **Paper X** and extract and refine condensed guidelines from literature and our experiences. **Papers XI and XII** provide examples of good mixed-methods research, also including configurational approaches that follows these guidelines.

	Goal 3: Develop condensed guidelines for using mixed-methods approaches within IS research, including qualitative, quantitative, and configurational approaches	
	Paper	**Research opportunities**
Chapter 3	Paper X	Condensed guidelines on conducting mixed-methods approaches, including configurational methods
	Paper XI	Example of the combination of qualitative and configurational methods
	Paper XII	Example of the combination of quantitative and configurational methods

Table 4. Summary of Methodological Research Opportunities

4 RESULTS

The WHO portrays IS use as an effective solution to health system overload, specifically recommending using social media, mobile apps and remote tools to foster mental health and AI-based applications to increase treatment capacities (e.g., WHO 2021b). Drawing from equivocal findings in IS literature concerning the burdening and releasing effects of IS on health system overload (e.g., Serrano and Karahanna 2016; Tarafdar et al. 2019b), this dissertation aims to offer insights into whether we can and should recommend an intensified IS use to solve health system overload. Our assessment in that regard is based on the logic of double effects (Monge and Hsieh 2020) and requires a dual approach, minimizing the burdening effects while unleashing the supporting effects. To this end, we present twelve research papers, with which we aim to pursue the three set research goals of this dissertation:

Goal 1: *Understand how IS use, specifically social media, mobile apps, and remote working tools, causes burdening effects on mental health and how to prevent them.*

Goal 2: *Identify pathways to successfully implementing AI-based chatbots in hospitals.*

Goal 3: *Develop condensed guidelines for using mixed-method approaches within IS research, including qualitative, quantitative, and configurational approaches.*

Section 4.1 presents the results of **Papers I to V**, contributing to the first goal. Section 4.2 shows the insights of **Papers VI to IX** gathered to fulfill the second goal, and section 4.3 displays our results tackling the third goal derived in **Papers X to XII**.

4.1 Chapter 1: IS Use and Mental Health

The intensified use of IS entails the risks of burdening individuals' mental health through negative emotions and technostress, which has received increasing attention in IS research over the last few years (Fischer and Riedl 2017). Here, we specifically focus on the stress potential of IS-enabled digital advertising options, such as influencer marketing in social media, in-app advertising, and remote work. Understanding the burdening effects stemming from these IS use contexts also helps gain insights on how to prevent the burdening effects, develop suited mitigations, and, eventually, make IS use part of the solution to health system overload.

4.1.1 Paper I: Information Overload and Presented Lifestyle in Social Media: A Stress-Perspective on the Effects on Mental Health[1]

To understand the stress potential of influencer marketing, **Paper I** uses social comparison theory (Festinger 1954) and theorizes a negative influence of two characteristics of influencer marketing. First, the information overload resulting from regularly issued influencer posts, and second, the overly luxurious presented lifestyle of influencers displayed in these posts. Confronting social media users with this successful and perfect lifestyle while presenting themselves as 'ordinary' people can elevate influencers to a standard of comparison, making them illegible for upward comparison (Chae 2018). When yielding a negative self-evaluation, this upward comparison can trigger negative emotions, such as frustration and envy, up to emotional exhaustion. The results of our quantitative SEM study (N= 152) show that those affective reactions foster social-media-induced depressive symptoms (R^2 = 0.594, moderate to high explanation). We also show that higher self-esteem, enabling us to bear or avoid the comparison (Vogel et al. 2014), and active use associated with better handling of incoming information and less negative feelings (Koroleva et al. 2010; Verduyn et al. 2015), can prevent influencer marketing's adverse effects on users mental health.

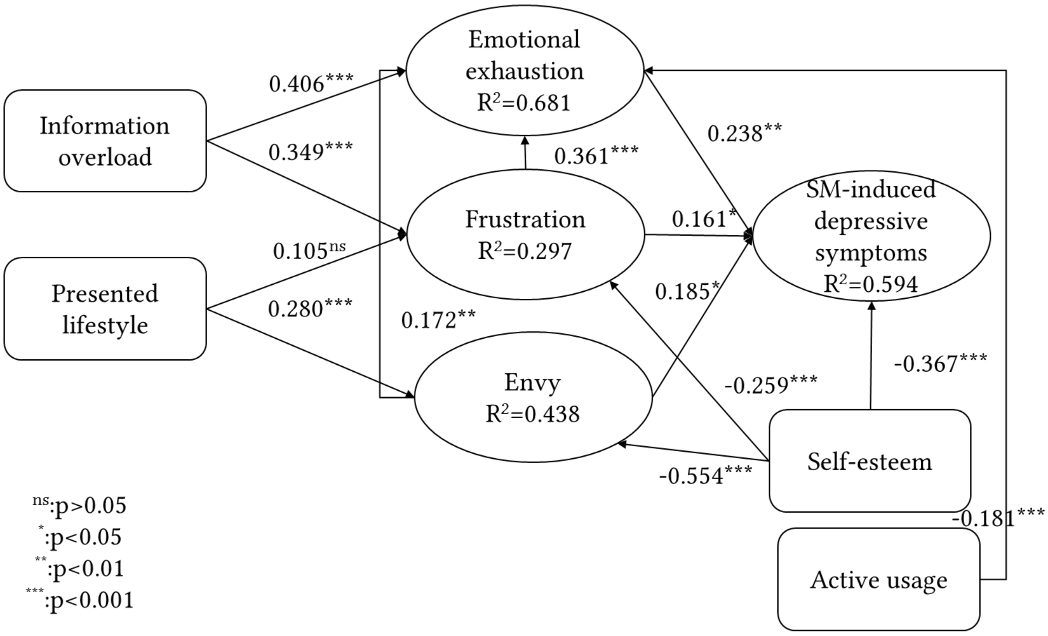

Figure 6. Paper I: Impact of Influencer Marketing on Depressive Symptoms (Reis 2022)

[1] Reis, Lea (2022): Information Overload and Presented Lifestyle in Social Media: A Stress-Perspective on the Effects on Mental Health; In: Proceedings of the 22nd ACM SIGMIS Conference on Computers and People Research, Atlanta (GA), United States

4.1.2 Paper II: In-App Advertising Stress and Coping Strategies: A Mixed-Methods Study [2]

Paper II leverages stress and coping research to conceptualize in-app advertising stress and the selection of associated coping responses. Our interviews (N=26) identified four in-app advertising stressors, interruption, irritation, privacy invasion, and undesired interaction, that can translate into emotional exhaustion and yield either a problem-focused control strategy (offline mobile app usage) or a problem-focused escape strategy (discontinuance of mobile app usage) as coping responses. Our two QCA analyses (see Figure 7 and Figure 8, N=205) confirm those findings, showing that each in-app advertising stressor contributes to selecting coping strategies in different combinations. Further, all three configurations yielding offline mobile app usage and three out of five configurations yielding the discontinuance of mobile app usage, identified emotional exhaustion contributing to this selection. This finding indicates that app users react adversely to present stressors and perceive strain. We, therefore, can conclude that in-app advertising causes in-app advertising stress. Further, the results show that app users perceiving the same in-app advertising stressors can still select different coping strategies depending on their willingness to oppose or escape in-app advertising. Also, in-app advertising stressors can yield proactive problem-focused escape strategies before an actual strain.

		High outcome (Offline)		**Low outcome (Offline)**
	C1'	**C2'**	**C3'**	**C4'**
Interruption		⊗	●	⊗
Irritation	●	●		⊗
Privacy invasion	●		●	⊗
Undesired interaction		●	●	⊗
Emotional exhaustion	●	●	●	⊗
Raw coverage	0.65	0.17	0.56	0.31
Unique coverage	0.11	0.01	0.03	0.31
Consistency	0.95	0.97	0.95	0.94
Solution coverage		0.946		0.31
Solution consistency		0.700		0.94

Note: Black circles (●) indicate high perceptions, white crossed-out circles (⊗) indicate low perceptions, and blank spaces ( ) indicate 'Don't care situations.' Black stars (★) indicate a necessary condition that needs to be high for a high outcome.

Figure 7. Paper II: Configurations of In-App Advertising Stressors and Strain Yielding Offline App Usage

[2] Reis, Lea; Maier, Christian; Mattke, Jens and Weitzel, Tim (2023): In-App Advertising Stress: A Mixed-Methods Study on In-App Stressors and Coping Strategies. Under Review at Computers in Human Behavior.

	High outcome (DISC)					Low outcome (DISC)
	C1	C2	C3	C4	C5	C6
Interruption		⊗	●	●	●	⊗
Irritation	●	●		●	●	⊗
Privacy invasion	●		●		●	⊗
Undesired interaction		●	●	⊗		⊗
Emotional exhaustion	●	●	●	⊗	⊗	⊗
Raw coverage	0.60	0.15	0.51	0.23	0.72	0.45
Unique coverage	0.03	0.01	0.03	0.01	0.07	0.45
Consistency	0.97	0.98	0.98	0.97	0.97	0.94
Solution coverage	0.827					0.45
Solution consistency	0.963					0.94

Note: Black circles (●) indicate high perceptions, white crossed-out circles (⊗) indicate low perceptions, and blank spaces ( ) indicate 'Don't care situations.' Black stars (★) indicate a necessary condition that needs to be high for a high outcome.

Figure 8. Paper II: Configurations of in-app advertising Stressors and Strain Yielding the Discontinuation of App Usage

Besides the identified coping reactions, app designers can also contribute to the prevention of stress stemming from in-app advertising. They can use natural usage pauses to display silent ad formats for highly targeted ads at a low frequency instead of random, interrupting content.

4.1.3 Paper III: A Mixed-Methods Study of Motivations in Mobile Ad-Blocker Use [3]

Papers I and II show that IS-enabled advertising involves the risk of reducing individuals' well-being and burdening their mental health. Among others, the interviews (N=44) in **Paper III** show that avoiding reduced well-being in response to mobile advertising can be an intrinsic motivation to install a mobile ad-blocker to prevent the exposure to stressful advertising.

	High intention	Low intention	
	C1	**C2**	**C3**
Reduced well-being through mobile ads	●	⊗	⊗
Improved privacy protection	●	⊗	⊗
Improved security	●	⊗	⊗
Improved user experience	●	⊗	●
Increased performance	●	⊗	●
Perceived reciprocity	⊗	●	●
Perceived mobile incompetence	⊗		⊗
Raw coverage	0.29	0.19	0.23
Unique coverage	0.29	0.08	0.11
Consistency	0.91	0.95	0.87
Solution coverage	0.29	0.30	
Solution consistency	0.91	0.89	

Note: Black circles (●) indicate the presence of a condition and crossed-out white circles (⊗)indicate the absence of a condition. Blank spaces ( ) indicate a 'Don't care situation,' in which the condition may be either present or absent and therefore plays a subordinate role

Figure 9. Paper III: Configurations of Motivations Yielding the Intention to Adopt Mobile Ad-Blockers

Our configurational analysis (N=249), as shown in Figure 9, shows that in combination with the intrinsic motivation, improved privacy protection, and the extrinsic motivations, improved security, improved user experience, and increase performance, reduced well-being contributes to a high intention to use mobile ad-blockers, given the absence of amotivation represented through perceived reciprocity and perceived mobile incompetence. Looking at the configurations for a low intention, we see that reduced well-being is absent in both configurations, indicating that only unstressed individuals show a low intention to use mobile ad-blockers. Thus, using mobile ad-blockers can be described as a problem-focused coping response to mobile advertising stress, combining control and escape strategies.

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[3] Reis, Lea; Maier, Christian; Mattke, Jens and Weitzel, Tim (2023): A Mixed-Methods Study of Intrinsic Motivation, Extrinsic Motivation, and Amotivation in Mobile Ad-Blocker Use. Under Review at the Journal of Advertising, prior version published at ICIS 2017 (Müller et al. (2017).

4.1.4 Paper IV: The Dark Side of Remote Work: A Mixed-Methods Study on Remote Work Stress [4]

Companies face the difficult decision of whether to offer remote work possibilities. On one hand, most employees only want to apply for remote flexibility jobs (Oliveros 2021). On the other hand, two out of three employees perceive the drawbacks of remote work, such as increased isolation, loneliness, and difficulties disconnecting from work (Robinson 2021). We contribute to this discussion and use interviews (N=22) to identify remote work stressors and adverse immediate and long-term remote work consequences (see Figure 10). Our results indicate that remote work stressors, namely role conflict, reduced communication quality, lack of appreciation, lack of perceived organizational support, lack of contact with supervisor or colleagues, and role overload, can yield adverse consequences regarding work exhaustion, job satisfaction, and the fear of rejection, which eventually influences employees' organizational commitment and perceived job performance (all R^2 show moderate to high explainability). This result is an essential insight for organizations, as they need to deal with the issue of remote work stress to avoid losing employees due to burnout or turnover (Ahuja et al. 2002; Maier et al. 2015a; Zaza et al. 2022).

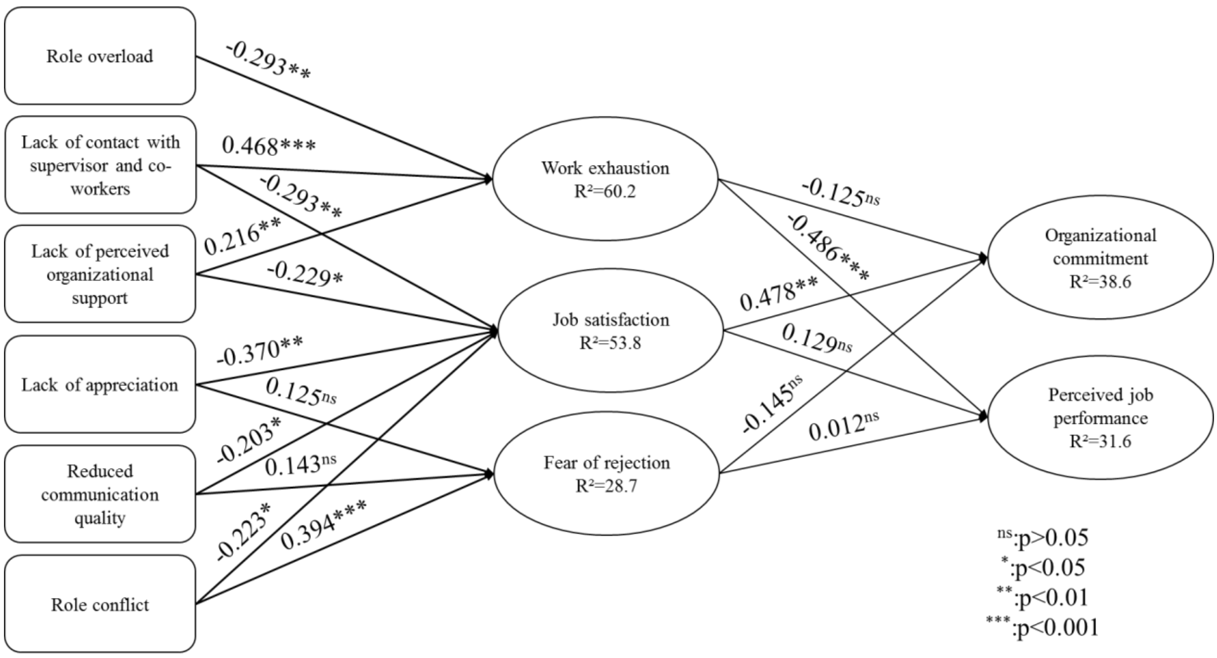


Figure 10. Paper IV: Remote work stress and its consequences

We advise organizations to proactively develop and implement a comprehensive remote work communication policy to mitigate the potential adverse effects of remote work. Many

[4] Reis, Lea; Maier, Christian; Beer, Felicitas and Weitzel, Tim (2023): The Downside of Working from Home: A Mixed-Methods Study on Remote Work Stress. Under Review at Information and Organization

employees desire clear directives regarding using specific communication tools and adopting best practices for remote work communication. These guidelines should encompass a commitment to utilizing video during video calls, encourage regular informal coffee chats between employees and supervisors, establish feedback mechanisms, and emphasize incorporating social elements into communication that may be lacking in video-supported or written exchanges. Furthermore, we recommend that organizations actively support their employees' transition to remote work by providing necessary equipment and offering guidance on reducing stress associated with remote work. This guidance may include suggestions on taking breaks, combating feelings of isolation, building self-discipline, and enhancing resilience. Lastly, organizations should utilize IS to motivate their remote employees. Organizations need to explore alternative means of fostering team cohesion and well-being in the absence of traditional office rewards like ordering pizza or sharing a coke in the kitchen. Possible initiatives could involve: (1) Implementing digital nudges to prompt employees to engage with their colleagues. (2) Organizing an organization-wide charity run or walk, allowing employees to accumulate miles as a team. (3) Providing vouchers for video-on-demand or audiobook platforms to help employees occupy their children or unwind. (4) Arranging for the delivery of fruit and vegetable boxes to support employees' health and well-being. These proactive measures can enhance remote work experiences and contribute to a positive and productive remote work environment.

4.1.5 Paper V: Unintended Consequences of Technostress Mitigation: An Employee Perspective on the Effectiveness of Mitigation Measures[5]

Employees increasingly feel overwhelmed by incoming requests and face difficulties disconnecting from work after hours (Bruijn 2021), which reduces their well-being and induces stress (Tarafdar et al. 2019b). The particular techno-stressors related to these observations are techno-overload and techno-invasion (Ragu-Nathan et al. 2008). To tackle these techno-stressors, examined organizations initiated eight mitigation measures, four addressing techno-invasion and four addressing techno-overload, which we categorize along three mitigation dimensions: technological, cultural, and social mitigation. Then, we assessed mitigation efficacy and unintended consequences by asking the IT employees how they perceived and experienced the mitigation methods.

Techno-stressor	Mitigation dimension	Mitigation measure
Techno-invasion	Technological	Separation of private and business devices
		Restriction of email traffic
	Cultural	Valuable pause culture – Introduction of an emergency channel
	Social	Valuable pause culture – Clear communication of expectations
Techno-overload	Technological	Good practices for internal communication
	Cultural	Introduction of 'pull not push' culture
	Social	Communication with executive
		Introduction of 'off-screen' communication opportunities

Table 5. Paper V: Overview of Identified Mitigation Measures (Reis et al. forthcoming)

Notably, our interview results (N=30) show that none of the mitigation measures is free of adverse effects for employees. Measures intended to mitigate one techno-stressor can have the unintended effect of fostering another, potentially failing to reduce overall technostress levels. This looping effect between techno-stressors and measures to mitigate them, combined with individual preferences regarding mitigation measures, shows that introducing successful mitigation measures requires a complex understanding of their effects on employees. Further, our results show that IT employees can also suffer from a specific stressor, namely IT responsibility that arises from the perceived burden of being aware of the responsibility for the IS implemented in the organization and of the potentially adverse consequences of IS-related decisions and systems for employees and their working routines.

[5] Reis, Lea; Maier, Christian; Pflügner, Katharina and Weitzel, Tim (2023): Unintended consequences of technostress mitigation: An employee perspective on the effectiveness of mitigation measures; Forthcoming in: The DATA BASE for Advances in Information Systems

4.2 Chapter 2: IS Use in Healthcare

The second facet of our research involves comprehending how the use of IS can support with reducing the burden on the healthcare workforce, making IS use part of the solution to health system overload. We specifically examine the use of AI-based chatbots in hospitals and outline sensible use cases and relevant user behaviors related to a successful implementation.

4.2.1 Paper VI: Chatbots in Healthcare: Status Quo, Application Scenarios for Physicians and Patients, and Future Directions[6]

With the help of interviews (N=23) and existing literature (e.g., Oh et al. 2017), we identified fourteen sensible use cases for implementing AI-based chatbots in hospitals from both the patient and physician perspectives. Three of those fourteen use cases stood out as most promising (see Figure 11, shaded boxes).

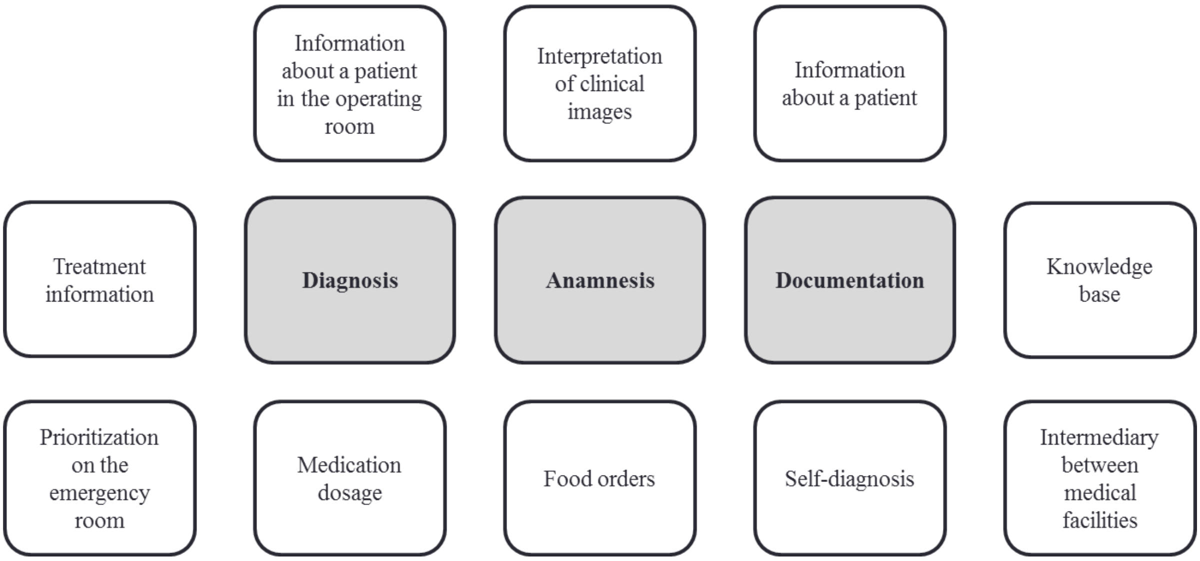


Figure 11. Paper VI: Sensible Use Cases for AI-Based Chatbots in Hospitals (Reis et al. 2020b)

Recent statistics (American Hospital Association 2020) indicate that physicians can spend only about 27 percent of their time with patients and are increasingly occupied with "secondary tasks," including patient monitoring and documentation. These secondary tasks lie outside the patient care field, are very time-intensive, and do not generate profit for the hospitals (Arndt et al. 2017). Consequently, hospitals aim to reduce the time clinical staff need to spend on secondary tasks by delegating secondary tasks to AI-based chatbots. For example, automating the common secondary task of documentation could give physicians approximately 49 percent of their working day back to be spent on patient care, which generates more money for hospitals, as, for example, one hour of treatment converts into two hours of documenting (Arndt et al.

[6] Reis, Lea; Maier, Christian and Weitzel, Tim (2020): Chatbots in Healthcare: Status Quo, Application Scenarios for Physicians and Patients and Future Directions, In: Proceedings of the 28th European Conference on Information Systems (ECIS)

2017). For the other two use cases, diagnosis and anamnesis, AI-based chatbots could provide the possibility of automated patient data gathering and analysis combined with a range of differential diagnoses. Recording and directly entering the gathered data into electronic health records could increase the accuracy and availability of data and decrease the risk of misdiagnoses. To realize the benefits assigned to those use cases for AI-based chatbots, patients and physicians must be willing to adopt the AI-based chatbot, which a significant portion is not, and respond with resistance. This behavior impedes the desired effect of relieving the health workforce (see Figure 12). To foster AI adoption, we must deal with both resistance and adoption behavior, which we do in **Papers VII and VIII**.

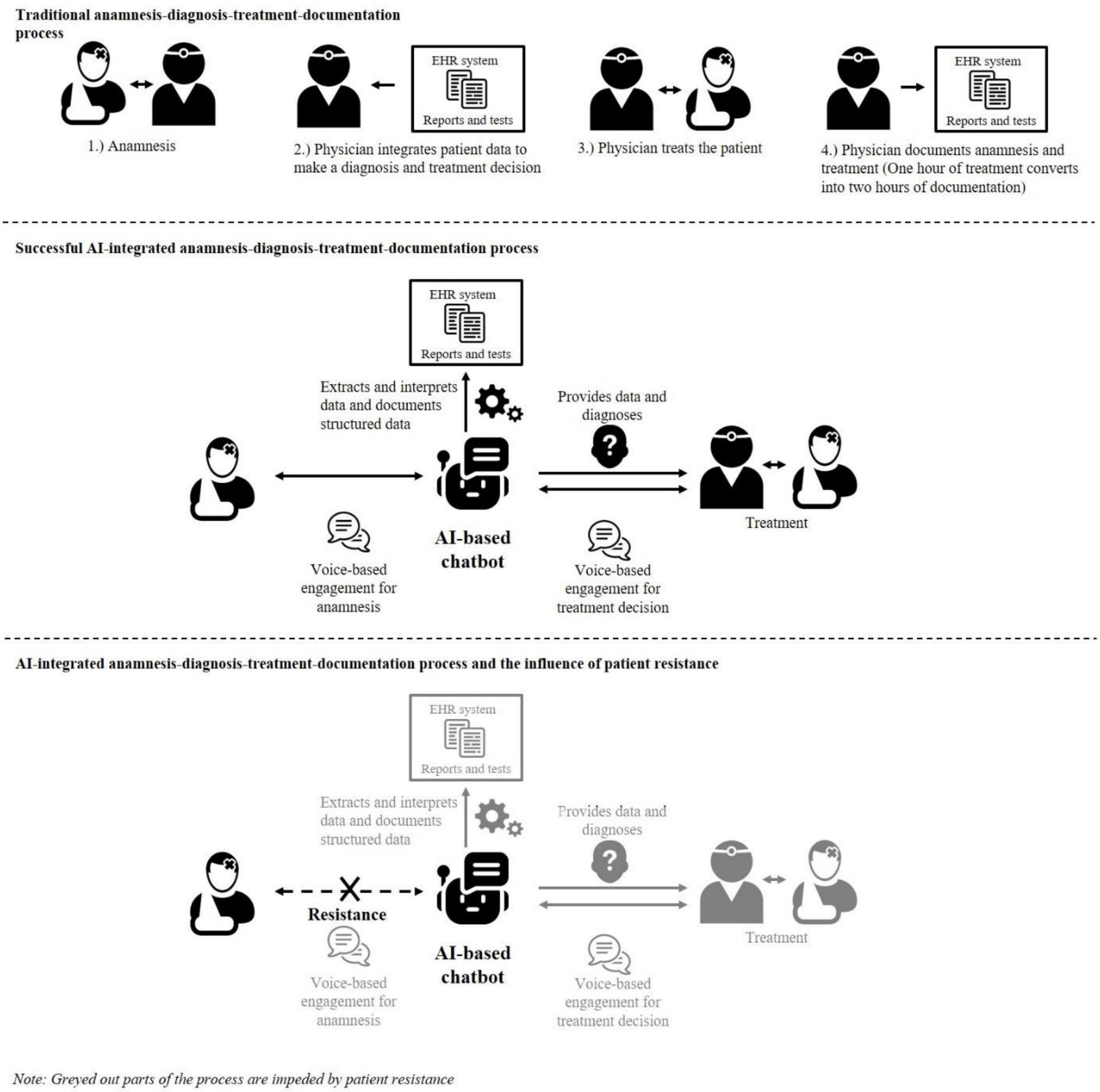


Figure 12. Successful and Unsuccessful Integration of AI-based Chatbots in the Anamnesis-Diagnosis-Treatment-Documentation Process (adapted from Reis et al. (2020a))

4.2.2 *Paper VII: Explaining Resistance to Using Chatbots in Healthcare: An Illustration of How to Include Configurational Approaches in Contextualized IS Research* [7]

With **Paper VII**, we provide the patients' perspective (N=175) on AI-based chatbots and offer configurations of contextualized factors from the status quo bias perspective, explaining their resistance to using AI-based chatbots for medical data collection during anamnesis (see Figure 13).

	High patient resistance				**Low patient resistance**
	$C1_{Ext}$	**$C2_{Ext}$**	**$C3_{Ext}$**	**$C4_{Ext}$**	**C_{Low}**
Transition costs	⊗	●		●	⊗
Uncertainty costs	⬤	⬤	⬤	⬤	⊗
Loss aversion	⊗		⊗	●	⊗
Sunk costs	⬤	⬤	⬤	⊗	●
Anticipated regret	●	●	●	●	⊗
Decision control	●	●	●	●	●
Distrust		⬤	⬤	⬤	⊗
Dispositional resistance to change	●	●		⊗	⊗
High frequency of consultations			⨂	⨂	⊗
Raw coverage	0.33	0.25	0.34	0.14	0.21
Unique coverage	0.05	0.04	0.03	0.03	0.21
Consistency	0.96	0.98	0.95	0.99	0.96
PRI consistency	0.90	0.95	0.89	0.97	0.79
Solution coverage	0.46				0.21
Solution consistency	0.95				0.96
PRI solution consistency	0.91				0.79

Note: Black circles (●) show high motivation, white crossed-out circles (⊗) show low motivation, and blank spaces ( ) indicate a 'Don't care situation.' In this case, the specific condition is irrelevant to the configuration and can either be high or low. Large circles indicate a core condition. Ext = extended high frequency of medical consultations.

Figure 13. Paper VII: Configurations Yielding Patient Resistance

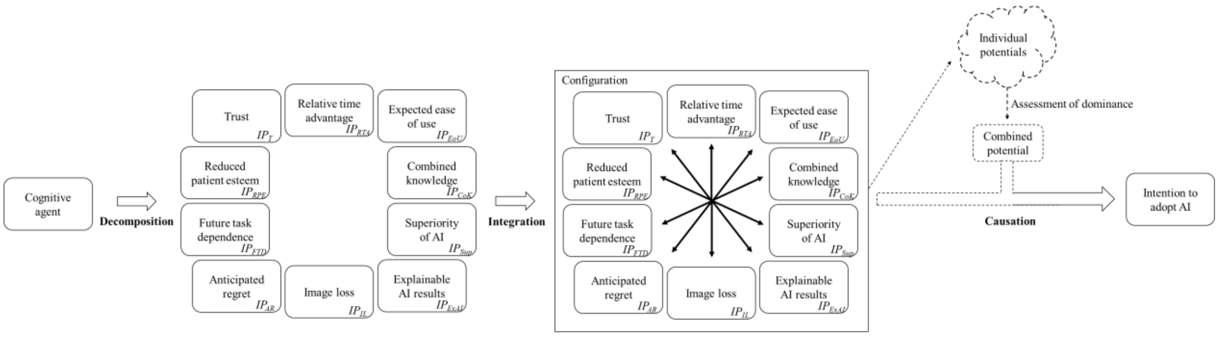
Upon closer examination of these configurations, it becomes evident that the lack of loss aversion is a prevalent factor. This finding implies that the resistance to AI-based chatbots is not rooted in a lack of potential advantages associated with their implementation. We consistently observe the presence of anticipated regret and uncertainty costs in all identified

[7] Reis, Lea; Maier, Christian; Mattke, Jens and Weitzel, Tim (2023): Explaining Resistance to Using Chatbots in Healthcare: An Illustration of How to Include Configurational Approaches in Contextualized IS Research. Under Review at the Information Systems Jounal, prior version published at Conversations 2019

configurations, leading to a high level of patient resistance. This insight suggests that patients are primarily concerned about the unforeseen negative consequences of utilizing AI-based chatbots for gathering medical data during anamnesis. Additionally, there is a sense of distrust in the performance of the AI-based chatbot in two out of three configurations. Hence, our findings highlight that the responsibility for the (limited) adoption of new IS in healthcare lies with physicians and patients. Interestingly, our results also indicate that the factors contributing to resistance against AI-based chatbots for medical data collection during anamnesis vary based on the number of consultations a patient undergoes annually. Notably, patients who experience a high frequency of consultations are also predisposed toward resistance to change. This finding may be associated with the habitual nature of repeated anamneses due to multiple consultations, a well-known influence on behavior in IS contexts (Polites and Karahanna 2012). In the case of configuration C_{1Ext}, dispositional resistance to change, when combined with anticipated regret, uncertainty costs, and sunk costs, even outweighs the perceived benefits, as evidenced by the absence of loss aversion and the perceived ease of use of the AI-based chatbot, denoted by the absence of transition costs. One possibility to increase trust is to improve the explainability of what the AI-based chatbot is doing, such that the patient can better anticipate the consequences of an AI-based chatbot integration. Another approach is to openly communicate the limitations of the functions provided by the AI-based chatbots. By clearly outlining that it serves as a supplementary tool for physicians, facilitating more efficient and comprehensive data collection, patients can be assured that it does not compete for valuable patient-physician interaction time or interfere with their treatment process.

4.2.3 Paper VIII: Artificial Intelligence in Healthcare: A Mixed Methods Study of Physicians' Chatbot Adoption Decision[8]

Adopting an AI-based chatbot represents a compelling prospect for hospitals to address the increasing healthcare demand. However, it also signifies a disruptive alteration to existing processes and workflows. To investigate whether physicians would adopt an AI-based chatbot, ultimately realizing the assigned benefits, we need to understand the process of forming the intention to adopt AI-based chatbots. Utilizing theories related to information processing and the adoption of IS (Campbell et al. 2016; Cenfetelli and Schwarz 2011), we propose a structured three-stage process: decomposition, integration, and causation (see Figure 14).



Note: he three-staged processing happens within one attempt in the human brain. Dashed lines and objects represent processes that are theorized, but not included into the measurement model but examined qualitatively.
IP = individual potential

Figure 14. Paper VIII: Decision Process of AI Adoption

In the decomposition phase, we analyze factors that facilitate or hinder the adoption of an AI-based chatbot. The identified enablers, namely trust, relative time advantage, expected ease of use, the superiority of AI results, complementary knowledge and explainable AI, and inhibitors, such as image loss, reduced patient esteem, anticipated regret, and future task dependence serve as input for the second phase, integration. During the integration phase, we investigate various combinations of these factors to determine their collective impact on the intention to adopt, employing a QCA approach (see Figure 15, N=154). Finally, in the causation phase, we identify prevalent combinations and employ interviews (N=16) to elucidate why physicians perceive them as dominant influences on their adoption decisions.

Specifically, we find that the combined potential for positive influence is driven by the presence of explainable AI results, the perceived superiority of AI, and the accumulation of knowledge and overcomes the individual potentials of present inhibitors. The explanation is that physicians are motivated by a desire to enhance the quality and safety of patient treatment, as well as the opportunity to mitigate potential adverse outcomes before they manifest. Conversely, we also

[8] Reis, Lea; Maier, Christian; Mattke, Jens and Weitzel, Tim (2023): Artificial Intelligence in Healthcare: A Mixed Methods Study of Physicians' Chatbot Adoption Decision. Pre-study published at DIGIT 2019, Best Paper Award

observe that a combined potential for negative influence is shaped by the absence of trust in AI, the lack of clear and understandable AI results, and individual factors such as anticipated regret and concerns about a negative impact on their professional image. Physicians are hesitant to adopt technology that does not offer clear benefits and could diminish their competence and professional standing. Furthermore, our findings reveal that the ethical responsibility of physicians for their patients can influence the weighting of these individual factors in the decision-making process. Physicians may prioritize different factors when making decisions solely for themselves, emphasizing those related to their benefit as dominant considerations.

	Combined potential yielding a high intention to adopt AI			**Combined potential yielding a low intention to adopt AI**
	C1	**C2**	**C3**	**C4**
Enablers				
Trust	★	★	★	⊗
Relative time advantage	●	●	●	⊗
Expected ease of use	●	●	●	
Complementary knowledge	★	★	★	⊗
Superiority of AI	●		●	⊗
Explainable AI results	★	★	★	⊗
Inhibitors				
Image loss	⊗	⊗		★
Anticipated regret		●	●	●
Future task dependence	●	●	●	●
Reduced patient esteem	●	●	●	●
Raw coverage	0.37	0.34	0.62	0.32
Unique coverage	0.34	0.03	0.31	0.32
Consistency	0.97	0.96	0.95	0.96
Solution coverage	0.71			0.32
Solution consistency	0.96			0.96

Note: Black circles (●) show high motivation, white crossed-out circles (⊗) show low motivation, and blank spaces ( ) indicate a 'Don't care situation.' In this case, the specific condition is irrelevant to the configuration and can either be high or low. Black stars indicate a necessary condition.

Figure 15. Paper VIII: Configurations of Enablers and Inhibitors Yielding AI Adoption

Our research underscores that physicians prioritize AI-related perceptions concerning the quality and safety of patient treatment, including trust, complementary knowledge, and explainable AI results when making decisions about adopting AI-based chatbots. To foster trust, we recommend employing trained individuals to educate the AI, allowing physicians to see the human expertise behind the system and promoting confidence in the AI's recommendations. Additionally, efforts should be made to enhance the explainability of AI results. Addressing complementary knowledge and the superiority of AI, it is essential to demonstrate that the AI functions as a colleague, not a competitor, and excels in tasks where physicians may be overqualified. This understanding reassures physicians, enabling them to confidently rely on AI support while focusing on patient care, which can translate into billable treatments for the hospital.

4.2.4 *Paper IX: Addressing User Resistance Would Have Prevented a Healthcare AI Project Failure*[9]

Paper IX treats the case of an unsuccessful implementation of an AI-based chatbot in a hospital and uses interviews (N=16) to examine that the primary causes of failure are rooted in users' resistance to the three types of AI: automation, decision support, and engagement (Davenport and Ronanki 2018). While each type offers benefits, they also introduce challenges, particularly in how users carry out their work routines. These alterations in work practices can trigger cognitive and emotional resistance among users, ultimately leading to a failed implementation. Therefore, when organizations embark on AI implementation, it is crucial to actively address and mitigate cognitive and emotional resistance associated with each type of AI.

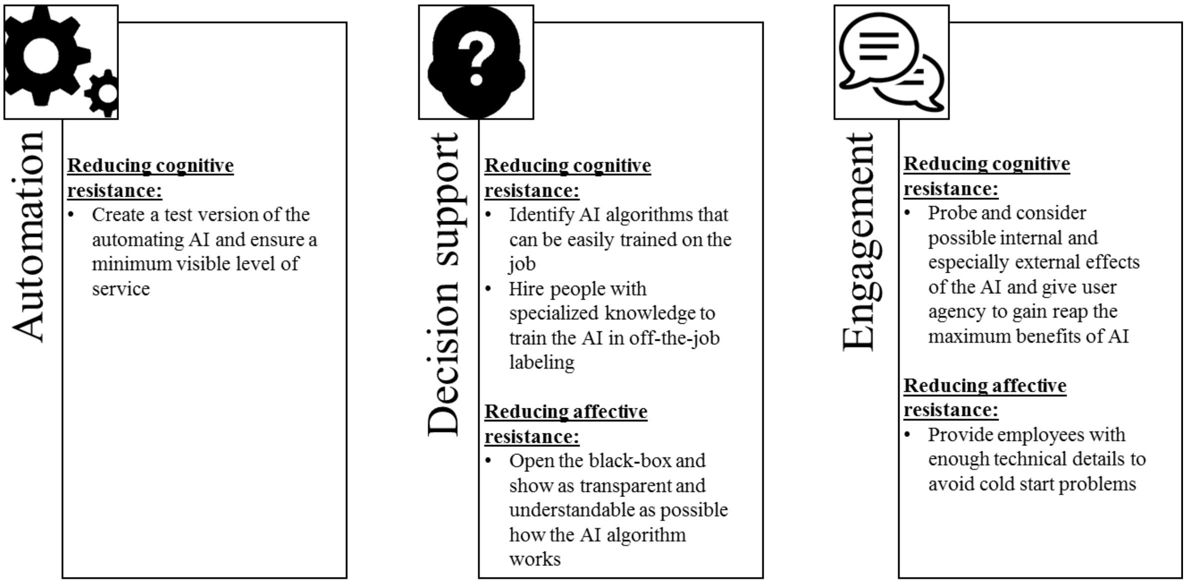


Figure 16. Paper IX: Pathways to a Successful AI-Implementation in Healthcare (Reis et al. 2020a)

Organizations should prioritize transparency by clearly communicating the capabilities and limitations of the AI application, commencing with a trial version. This approach helps cultivate realistic expectations and enhances the comprehensibility of the application. Organizations can further safeguard against AI implementation failures by (1) employing individuals with specialized knowledge in the relevant application domains to support machine learning, (2) adhering to a gradual implementation strategy, implementing AI one step at a time, and (3) maintaining open and transparent communication regarding the AI's intended applications and anticipated internal and external impacts. These actions collectively contribute to a more successful and effective AI implementation.

[9] Reis, Lea; Maier, Christian; Mattke, Jens; Creutzenberg, Marcus and Weitzel, Tim (2020): Addressing User Resistance Would Have Prevented a Healthcare AI Project Failure, In: MIS Quarterly Executive (19:4), Article 8

4.3 Chapter 3: Mixed-Methods in IS Research

By applying and drawing upon our theoretical understanding of mixed-methods approaches, we have observed numerous efforts to enhance the practicality of guidelines for conducting mixed-methods in IS research (Siponen et al. 2021; Walsh 2015). Those attempts have remained only partly successful. In **Paper X**, we aim to take on this opportunity by distilling and refining concise guidelines from existing literature and our own experiences. Furthermore, **Papers XI and XII** serve as illustrative instances of sound mixed methods research applications that adhere to these guidelines and demonstrate how to incorporate configurational approaches, where prior research has focused the combination of qualitative and quantitative approaches (Venkatesh et al. 2013).

4.3.1 Paper X: Mixed-Methods in Information Systems Research: Status Quo, Core Concepts, and Future Research Implications[10]

Literature has provided three core concepts for conducting mixed methods research: purpose, meta-inferences, and validation (Venkatesh et al. 2016; Verhagen et al. 2015). However, prior literature has not yet provided practicable implementation guidelines (Siponen et al. 2021; Verhagen et al. 2015; Walsh 2015; Yu and Khazanchi 2017). **Paper X** provides these condensed, practicable guidelines (see Figure 17).

Once authors have identified one or more suitable research purposes, the next step is carefully considering the appropriate research design that aligns with the selected purpose(s). For instance, a developmental or expansion purpose often necessitates a sequential study design, while completeness and compensation purposes can be effectively pursued using a concurrent design. Furthermore, authors should be mindful of the paradigmatic assumptions underlying their research inquiry. While it is not essential to delve into extensive details regarding these assumptions, it is crucial to remember how knowledge is derived and what is deemed as reality to yield pertinent results. These paradigmatic assumptions can also be instrumental in deducing meta-inferences, encompassing the combined knowledge derived from conducting two methods within a single inquiry. We recommend explicitly stating these meta-inferences and discussing convergent, complementary, and discordant inferences from both combined methods. Authors can underscore the advantages and necessity of employing this methodological combination. We also strongly advise authors to provide thorough validations for all inferences, including validating meta-inferences. This comprehensive validation ensures

[10] Reis, Lea; Maier, Christian and Weitzel, Tim (2022): Mixed-Methods in Information Systems Research: Status Quo, Core Concepts, and Future Research Implications, In: Communications of the Association for Information Systems, 51

the robustness of the derived inferences, the theoretical assumptions concerning the phenomenon, and the underlying causality.

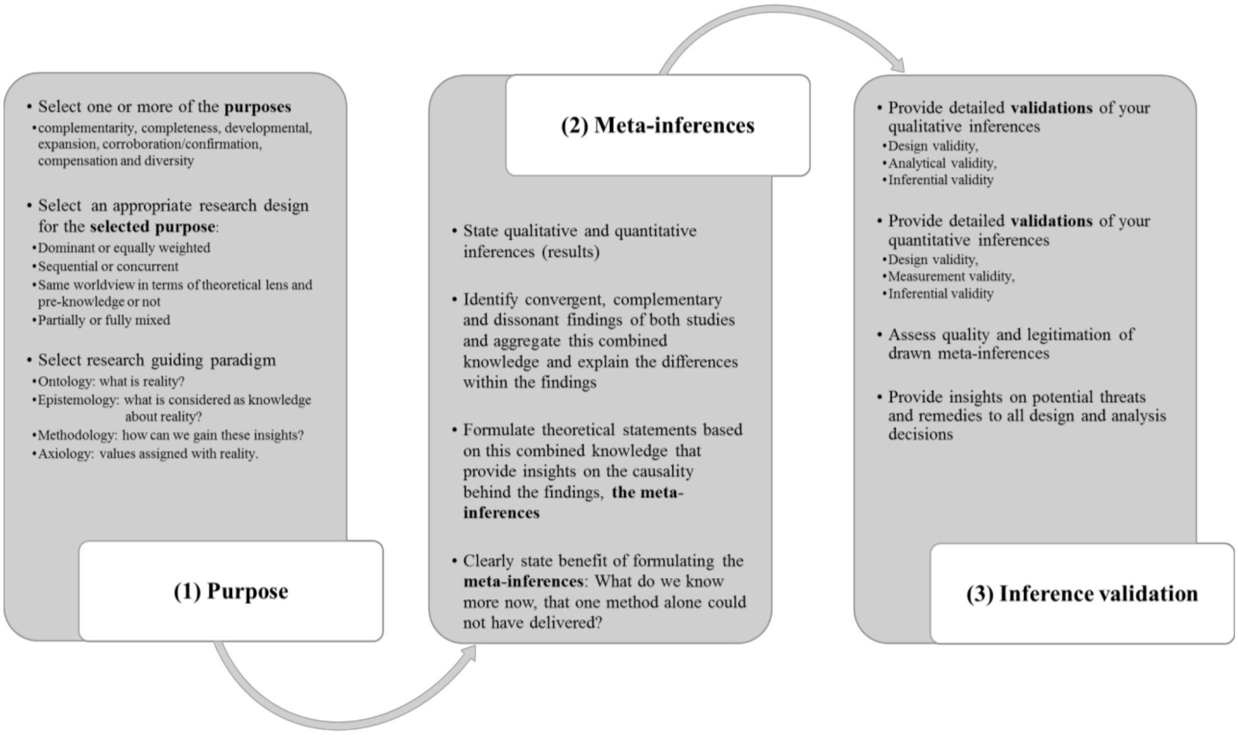


Figure 17. Paper X: Mixed-Methods in a Nutshell (Reis et al. 2022b)

Our condensed guidelines provide authors with a structured framework to deliver results that can best benefit IS research. Furthermore, we present a structured overview of mixed-methods research within the IS field as an initial reference point for upcoming studies. Additionally, we conduct quantitative analyses of the selected papers, which offer valuable insights into developing mixed-methods studies in IS research in light of existing guidelines. These insights are particularly pertinent for review boards evaluating submitted mixed-methods work. While not all papers strictly adhered to a structured mixed-methods approach, they still yielded noteworthy contributions to IS research. In light of the ongoing debate on whether research guidelines should be viewed as rigid regulations (Siponen et al. 2021), we encourage reviewers to leverage the findings of this study. Reviewers should not only recommend compliance with guidelines but also assist authors in optimizing their mixed-methods studies to present their assets most effectively. The core concepts, along with insights on their application, can serve as guiding principles for evaluating mixed-methods studies in the future. This approach ensures that quality research can still be published even if it does not conform to all existing guidelines. Our presentation of the current landscape demonstrates that while authors may not need to incorporate all core concepts, considering them and reflecting on their impact can enhance the paper's quality and underscore the valuable contributions it offers to IS research.

4.3.2 Paper XI: Bitcoin Investment: A Mixed-Methods Study of Investment Motivations[11]

Paper XI offers an example of a developmental mixed-methods approach, combining a qualitative interview study (N=73) with a configurational QCA analysis (N=150) within a sequential mixed-methods approach in the context of cryptocurrencies (Mattke et al. 2020a, 2020b). The purpose of the mixed-methods approach lies in the explorative identification of bitcoin investment motivations and the simultaneous analysis of configurational relationships between the factors and with the bitcoin investment decision. Due to the combined analysis, we could derive four configurations representing four investor types. Our results indicate that some investors invest in bitcoin because they support the ideology without any expectation of profit (see Figure 18). As such, **Paper XI** depicts a model study for developmental mixed-methods.

	The incompatible profit investor	**The risk affine profit investor**	**The not-profit-driven ideological investor**	**The experienced ideological investor**
Perception of the investment object				
Profit expectancy	●	●	⊗	●
Ease of bitcoin acquisition	●	●	●	
Support of bitcoin ideology	⊗		●	●
Personal factors				
Investment skills	★	★	★	★
Risk affinity		●	●	●
Regret sentiments				
Experienced inaction regret			●	●
Anticipative inaction regret	●	●		●
Raw coverage	0.33	0.42	0.41	0.64
Unique coverage	0.02	0.03	0.02	0.25
Consistency	0.93	0.96	0.97	0.97
Solution coverage	0.70			
Solution consistency	0.95			

Note: Black circles (●) show high motivation, white crossed-out circles (⊗) show low motivation, and blank spaces ( ) indicate a 'Don't care situation.' In this case, the specific condition is irrelevant to the configuration and can either be high or low. Black stars indicate a necessary condition.

Figure 18. Paper XI: Configurations of Motivations Leading to Bitcoin Investment (Mattke et al. 2020c)

[11] Mattke, Jens; Maier, Christian; Reis, Lea and Weitzel, Tim (2021): Bitcoin investment: A mixed methods study of investment motivations, In: European Journal of Information Systems, 30:3, 261-285

4.3.3 *Paper XII: Challenge and Hindrance IS Use Stressors and Appraisals: Explaining Contrarian Associations in Post-Acceptance IS Use Behavior*[12]

Paper XII illustrates a mixed-methods approach combining quantitative and configurational studies (N=178) in the context of challenge and hindrance IS use stress. Following a sequential expansion approach, the paper first develops and validates hypotheses with SEM and then investigates inconclusive findings with a QCA approach (see Figure 19).

	High		**Low**	
	Routine use	**Innovative use**	**Routine use**	**Innovative use**
Stressors				
Challenge IS use stressor	●	★	⊗	⊗
Hindrance IS use stressor			●	●
Personal factors				
Challenge IS use appraisal	●	★	⊗	⊗
Hindrance IS use appraisal			●	●
Coverage	0.93	0.96	0.77	0.75
Consistency	0.91	0.77	0.99	0.92

Note: Black circles (●) show high motivation, white crossed-out circles (⊗) show low motivation, and blank spaces ( ) indicate a ‘Don’t care situation.’ In this case, the specific condition is irrelevant to the configuration and can either be high or low. Black stars indicate a necessary condition.

Figure 19. Paper XII: Configurations of Challenge and Hindrance Stressors and Appraisals Yielding Routine or Innovative IS Use (Maier et al. 2021)

Due to the combination of both studies, we reveal knowledge beyond the scope of each approach. Specifically, the quantitative findings reveal that challenge IS use stressors positively mediate in facilitating routine use, and innovative use through challenge IS use appraisal. The QCA outcomes confirm and complement these insights by highlighting that challenge IS use stressors and challenge appraisal are essential for routine use and for fostering high levels of innovative use. Therefore, we can conclude that challenge IS use stressors contribute to promoting routine use and innovative use through challenge IS use appraisal. Additionally, both challenge IS use stressors, and challenge IS use appraisal are indispensable for driving innovative use. Moreover, the quantitative results indicate that hindrance IS use stressors negatively mediate routine use through appraisal of hindrance IS without affecting innovative use. Although the QCA results corroborate the impact on routine use, they indicate that hindrance IS use stressors can lead to reduced innovative use through hindrance IS use appraisal

[12] Maier, Christian; Laumer, Sven; Tarafdar, Monideepa; Mattke, Jens; Reis, Lea and Weitzel, Tim (2021): Challenge and Hindrance IS Use Stressors and Appraisals: Explaining Contrarian Associations in Post-Acceptance IS Use Behavior, In: Journal of the Association for Information Systems, 22(6), 1590-1624.

if challenge IS use stressors and appraisal are absent. Hence, we can conclude that hindrance IS use stressors impede both routine use and innovative use through hindrance IS use appraisal, especially when challenge IS use stressors and appraisal are absent. As such, **Paper XII** can serve as a model study for successfully applying an expansion mixed-methods approach with quantitative and configurational methods.

4.4 Summary

Working on the question of whether intensified IS should be recommended to solve health system overload, based on inconclusive findings in the IS literature regarding the burdening and supporting effects (e.g., Serrano and Karahanna 2016; Tarafdar et al. 2019b), this dissertation endeavors to provide valuable insights into making IS use part of the solution. To achieve this objective, we introduce a collection of twelve research papers, contributing to the three goals of this dissertation in three chapters. With this, we offer a double-barrel approach, minimizing the burdening effects while unleashing the supporting effects. This approach grounds on a methodological pluralism, involving literature reviews, qualitative interviews, quantitative surveys, configurational studies, and mixed-methods approaches, allowing us to tackle our two theoretical and one methodological research opportunities (see Table 2 and Table 4). Table 6 provides an overview of the obtained results.

	Goal 1: Understand how IS use, specifically social media, mobile apps, and remote working tools, causes burdening effects on mental health and how to prevent them		
	Paper	**Burdening effects**	**Mitigations**
Chapter 1	**Paper I**	Information overload and the presented lifestyle of influencer marketing yield envy, frustration, and emotional exhaustion, eventually fostering depression.	Higher self-esteem and active social media usage can reduce these effects.
	Paper II	In-app advertising yields stress reactions. We identified interruption, irritation, privacy invasion, and undesired interaction as in-app advertising stressors and emotional exhaustion as in-app advertising strain. Depending on the configuration, these stressors and the resulting strain yield either a problem-focused control strategy (offline mobile app usage) or a problem-focused escape strategy (discontinuance of mobile app usage) as coping responses.	App designers can contribute to the prevention of stress stemming from in-app advertising. For example, they can use natural usage pauses to display silent ad formats for highly targeted in-app ads at a low frequency instead of random content interrupting users.
	Paper III	Mobile advertising is stressful and reduces mobile device users' well-being.	Ad-blocker usage can be seen as a problem-focused coping response to stressful exposure to mobile advertising.

	Paper IV	Remote work stressors, namely role conflict, reduced communication quality, lack of appreciation, lack of perceived organizational support, lack of contact with supervisor or colleagues, and role overload, can yield adverse consequences regarding work exhaustion, job satisfaction, and the fear of rejection, which eventually influences employees' organizational commitment and perceived job performance.	Successful remote work stress mitigations include a clear communication of directives regarding the use of specific communication tools, a guided transition into remote work, and new incentives for employees working from home.
	Paper V	Techno-overload and techno-invasion increasingly burden employees' well-being. IT employees can suffer from a specific stressor, namely IT responsibility, that arises from the perceived burden of being aware of the responsibility for the IS implemented in the organization and the potentially adverse consequences of IS-related decisions and systems for employees and their working routines. Techno-overload and techno-invasion can foster IT responsibility.	Successful mitigation requires a combined approach of technological, social, and cultural mitigations and a detailed understanding of employees' needs. Inappropriate mitigations can have harmful effects, and some mitigations reducing one stressor can foster another, causing looping effects.
Chapter 2	**Goal 2: Identify pathways to successfully implementing AI-based chatbots in hospitals**		
	Paper	**Use cases for AI-based chatbots**	**User behavior related to a successful implementation**
	Paper VI	We identified fourteen use cases for AI-based chatbots, with anamnesis, diagnosis, and documentation bearing the most potential.	
	Paper VII	Anamnesis and documentation.	Patient resistance does not arise from a lack of benefits but concerns about the unforeseen negative consequences of utilizing AI-based chatbots and distrust. To overcome this resistance, hospitals can advance the chatbot results' explainability and outline the chatbot's limited functions as a support tool.
	Paper VIII	Anamnesis-diagnosis-treatment-documentation process.	Physicians' adoption decision happens in three stages: decomposition, integration, and causation. Our research underscores that physicians prioritize AI-related perceptions concerning the quality and safety of patient treatment, including trust, complementary knowledge, and explainable AI results when making decisions about adopting AI-based chatbots. The ethical responsibility of physicians for their patients shapes the weighting of individual factors in the decision-making process.

<table>
<tr><td></td><td>Paper IX</td><td>Anamnesis-diagnosis-treatment-documentation process.</td><td>Alterations in physicians’ work practices can trigger cognitive and emotional resistance, ultimately leading to a failed implementation of AI-based chatbots. To address the resistance and prevent AI implementation failures, hospitals should begin with a trial version of the AI application to communicate its capabilities and limitations transparently, fostering realistic expectations. Further, they should hire domain experts to support machine learning, implement AI incrementally, one step at a time, and maintain open, transparent communication about the AI's intended impacts.</td></tr>
<tr><td rowspan="7">Chapter 3</td><td colspan="3">Goal 3: Develop condensed guidelines for using mixed-method approaches within IS research, including qualitative, quantitative, and configurational approaches</td></tr>
<tr><td>Paper</td><td colspan="2">Development of guidelines</td></tr>
<tr><td>Paper X</td><td colspan="2">Based on a comprehensive examination of 52 papers that employ mixed-methods in IS research, we offer the following recommendation to significantly enhance the rigor and comprehensiveness of mixed-methods research: (1) Begin with a clear understanding of your research purpose: Determine what you aim to accomplish by combining studies from different research paradigms in terms of contributions. (2) Choose a research design aligned with your purpose: Select the design features that best align with your research objectives. (3) Emphasize the essence of paradigms: Rather than dwelling extensively on paradigms, focus on capturing their fundamental aspects. Challenge any pre-existing positivist or constructivist inclinations and remain receptive to the potential contributions of alternative research paradigms. Strive to construct a combined reality from the different paradigmatic approaches. (4) Explicitly articulate meta-inferences in a dedicated section: Meta-inferences encapsulate knowledge that cannot be derived from either study in isolation. Discuss the convergent, complementary, and discordant findings, and formulate statements elucidating the reasons behind these observations. (5) Validate all inferences meticulously: Furnish comprehensive validation for all facets of your mixed-methods study, encompassing inferences derived from the studies and meta-inferences. This validation encompasses aspects such as data collection, data quality, research methods, and the deduction of inferences.</td></tr>
<tr><td></td><td colspan="2">Examples of Mixed-Methods Approaches in IS Research</td></tr>
<tr><td>Paper XI</td><td colspan="2">Illustrative example of a developmental mixed-methods approach in the context of bitcoin investment, taking the epistemological perspective of pragmatism. The paper integrates a qualitative interview study with a configurational QCA analysis in a sequential mixed-methods design.</td></tr>
<tr><td>Paper XII</td><td colspan="2">An illustrative example of an expansion mixed-methods approach in the context of challenge and hindrance IS use stress, taking the epistemological perspective of critical realism. The paper integrates a quantitative SEM study with a configurational QCA analysis in a sequential mixed-methods design.</td></tr>
</table>

Table 6. Overview of Results

5 DISCUSSION

Health system overload is a striking problem for many countries worldwide (WHO 2023). In a nutshell, health system overload occurs due to a rise in treatment requests or a decrease in treatment capabilities, such that the current healthcare resources are insufficient to deal with the demand (Watson et al. 2013). While the WHO recommends intensified IS use, specifically social media, mobile apps, remote tools, and AI-based applications, as a remedy (e.g., WHO 2021b), the literature currently presents equivocal findings concerning the role of IS in health system overload. On one hand, IS can lead to technostress, negatively affecting well-being and performance (Benlian 2020; Ragu-Nathan et al. 2008; Tarafdar et al. 2019b) that eventually can harm physical and mental health (Becker et al. 2022; Maier et al. 2019; Maier et al. 2022), potentially overloading the health system. On the other hand, IS can support the healthcare sector. AI-based applications, for example, can alleviate the deficit in the health workforce (Hao 2020; Reis and Maier 2022; Serrano and Karahanna 2016), reducing healthcare costs and freeing up resources. However, their adoption remains slow (Gartner 2019), limiting their potential to mitigate health system overload (McKinsey 2020).

Digging into the dual nature of IS use in health system overload, this dissertation provides twelve research papers that contribute to the discussion of the role of the recommended IS and, based on the logic of double effects (Monge and Hsieh 2020), aim to minimize the burdening effects while unleashing the supporting effects. **Papers I to V** provide further insights into the burdening effects of IS use, specifically focusing on the contexts of IS-enabled advertising and remote work. We offer methods to mitigate, reduce, and prevent these burdening effects. **Papers VI to IX** illustrate how AI-based chatbots can relieve and support the health workforce, specifically physicians, during the anamnesis-diagnosis-treatment-documentation process. Focusing on relevant user behaviors, namely adoption and resistance, we provide recommendations on preventing AI implementation failure and fostering adoption to realize the associated benefits. With **Papers X to XII**, we strengthen our results' methodological rigor and reliability, providing condensed guidelines for conducting mixed-methods approaches that were followed in this dissertation. Providing a methodologically sound double-barreled approach that simultaneously lowers the burdening effects while unleashing the supporting effects, we can conclude that, if monitored closely and implemented successfully, IS can be part of the solution to health system overload.

Leveraging the insights of the twelve papers, this cumulative dissertation provides multiple contributions to theory, methodology and implications for practice. These contributions and implications are summarized in the following sections, followed by limitations and future research opportunities.

5.1 Theoretical and Methodological Contributions

This section presents the theoretical contributions provided by this dissertation. With the **Introductory Paper**, we offer a double-barreled approach to understanding the dual nature of IS and making IS use part of the solution to health system overload, with which we contribute to research treating the logic of double effects (Monge and Hsieh 2020) and to research treating health system overload (Watson et al. 2013) (see Figure 20).

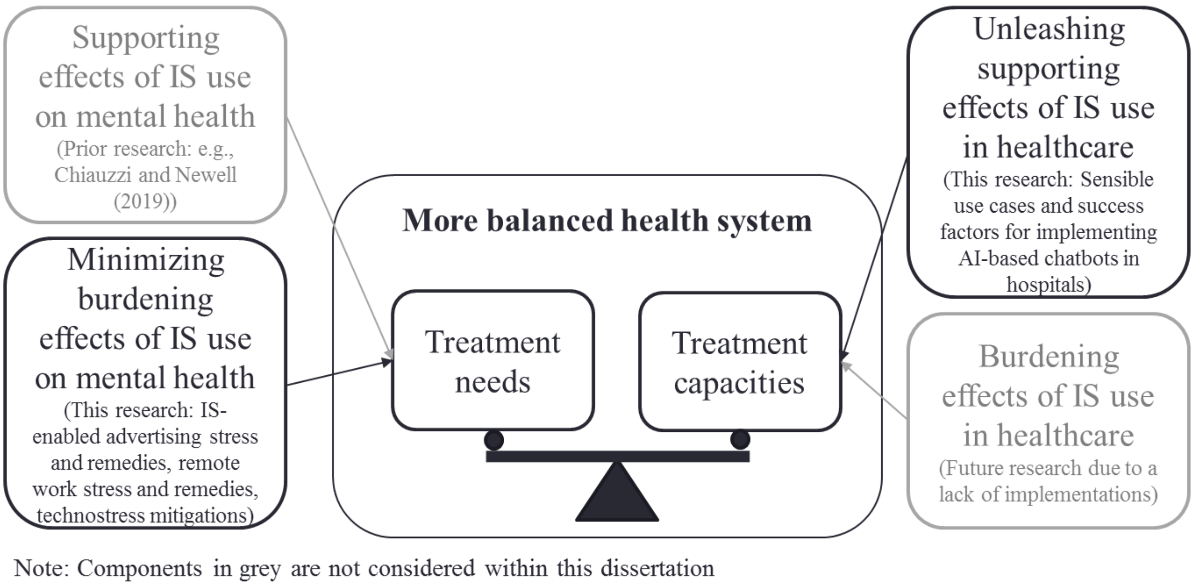


Figure 20. Contributions to Making IS Use Part of the Solution to Health System Overload

Specifically, we contribute to research treating health system overload by providing an empirically validated approach to reducing health system overload with the use of IS that goes beyond the sheer recommendation and discovery of potentials (e.g., WHO 2021a). While prior research has evaluated management-oriented approaches (Patrick and Puterman 2008), we specifically consider the use of IS and weigh their equivocal effects in contributing to health system overload before deciding against or in favor of a recommendation. We base this assessment on the logic of double effects (Monge and Hsieh 2020), with which be contribute to ethics research by contextualizing this moral logic in the context of health system overload. While prior research has used the logic of double effects to ethical dilemmas in war, bioethics and business research (Monge and Hsieh 2020), we use it to determine whether recommending the intensified use of IS to overcome health system overload is morally acceptable, contributing a new application field. From this contextualization, we deduce that we should only recommend the intensified use of IS to overcome health system overload, if we can minimize the unintended burdening effects and unleash the intended supporting effects, such that the benefits can outweigh the potential burden on health system overload. With this, we contribute a specific body of research opportunities and assessment criteria to future research aiming to contribute IS-enabled solutions to health system overload beyond the scope of recommended IS treated in this dissertation.

Besides these contributions on an aggregated level, we also contribute on the paper level to understanding the role of IS in health system overload. We structure the theoretical contributions derived from our twelve research papers according to the three research goals of this dissertation into contributions to research concerning understanding the burdening effects of IS use, contributions to research concerning insights on the supporting effects of IS use, and contributions to mixed-methods research.

5.1.1 Theoretical Contributions: Burdening Effects of IS Use on Mental Health

With our results, we make multiple contributions to technostress, advertising, and remote work research. We outline those contributions in more detail below.

Contributions in the Research Context of IS-Enabled Advertising Stress Establishing a New Research Stream. Papers I to III tackle the burdening effects of influencer marketing, in-app advertising, and mobile advertising. The stress potential of advertising, transmitted through the use of IS and mobile devices, has, so far, neither been treated in technostress nor advertising research and therefore contributes a new sub-stream of literature examining the dark side of IS-enabled advertising at the intersection of both streams. Specifically, we show that the presented lifestyle of influencer marketing (**Paper I**) and the identified in-app advertising stressors interruption, irritation, privacy invasion, and undesired interaction (**Paper II**) trigger a stress reaction yielding emotional exhaustion. While exhaustion has been a well-studied consequence in other advertising domains, such as consumer confusion (Walsh et al. 2007; Wang and Shukla 2013), and with technostress resulting from IS usage (Maier et al. 2012), we now trace the reaction back to overwhelming emotions in response to advertising stressors. This contributes to technostress research by identifying a new class of IS-mediated stressors and to advertising research by shedding light on the dark side of advertising. Further, we contribute to both streams by identifying mitigations to reduce the burdening effects of IS-enabled advertising.

Contributions in the Research Context of IS-enabled Advertising Stress to IS Use Behavior Research. In addition to proving the stress potential of in-app advertising, **Paper II** identifies related coping responses. Specifically, we identify offline mobile app usage as a problem-focused control strategy and the discontinuance of mobile app usage as a problem-focused escape strategy (Latack and Havlovic 1992). Further, **Paper III** describes mobile ad-blockers as a mixture of problem-focused escape and control strategies. In each case, the stressful nature of the received advertising causes the user to change her IS use behavior. While the intention to discontinue IS usage has previously been explored in technostress research (LePine et al. 2004; Maier et al. 2015c), these studies have primarily focused on the relationship between stress caused by specific features of IS and the intention to stop using that particular IS. Our research, on the other hand, demonstrates that IS-enabled advertising stressors, leading to emotional exhaustion, affect the use of mobile devices and apps through offline app usage, the discontinuance of mobile apps, or the adoption of mobile ad-blockers. This discovery suggests a spillover effect of advertising stress on IS usage. In essence, IS-enabled advertising stressors contribute to IS use behavior changes. For future technostress research, scholars should consider IS features as sources of stress and examine the services associated with the IS, such as advertising in apps, to elucidate how stress influences user behaviors.

Contributions to the Research Context of Remote Work Stress in Distinction to Work and Technostress. Existing literature has not explicitly identified remote work stressors and their associated consequences. It draws from broader research on work stress (Ahuja et al. 2002) or technostress (van Zoonen et al. 2021) to explain remote work stress. **Paper IV** enhances this understanding by presenting a remote work stress model that captures the distinct characteristics of remote work stress, six specific stressors, and their resulting adverse effects. Three of the identified stressors are specific remote work stressors—reduced communication quality, lack of appreciation, and lack of organizational support—that shed light on the unique challenges faced by remote employees. While work exhaustion and job satisfaction are well-studied outcomes of work stress (Moore 2000), we contribute by highlighting the fear of rejection as a specific consequence of remote work stress stemming from the potential for social isolation. In conjunction with the identified remote work stressors, we demonstrate that this fear adds to the social dimensions of remote work stress, extending beyond issues of role conflict and lack of contact, which can also apply to on-site work (Moore 2000). These additional stressors and the fear of rejection may explain why remote workers are prone to experiencing stress-related mental health symptoms more so than on-site employees (Mann and Holdsworth 2003).

Contributions to Technostress Mitigation Research. Employees feel increasingly stressed by techno-overload and techno-invasion. **Paper V** identifies eight mitigation measures, which we categorized as technological, social, or cultural mitigation measures. These findings go beyond insights from earlier studies focusing on technological mitigation measures (Galluch et al. 2015). Further, we expand technostress mitigation research advertising for specific mitigations for specific techno-stressors (Valta et al. 2021) by stressing the importance of taking a multidimensional approach to mitigating technostress that considers the technological, cultural, and social aspects of technostress. Additionally, **Paper V** proves the individuality of technostress mitigation by outlining the specifics for IT professionals, such as the specific techno-stressor techno-responsibility, and identifies the particular risk of yielding adverse effects with inappropriate mitigation measures. In the extreme, mitigations directed at reducing one stressor can foster another, creating looping effects (see Figure 21).

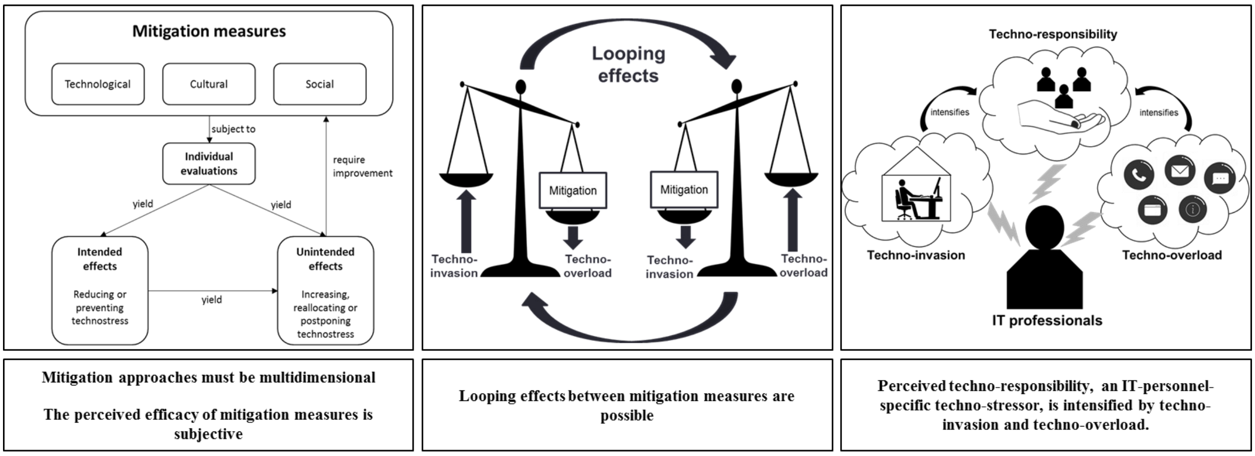


Figure 21. Paper V: Contributions to Technostress Mitigation (adapted from Reis et al. forthcoming)

5.1.2 Theoretical Contributions: Supporting Effects of IS Use in Healthcare

Our findings offer several valuable contributions to chatbot and healthcare research, which we elaborate on in the following sections.

Contributions to the Research Context of AI-based Chatbots in Healthcare. The shortage of qualified personnel in the healthcare sector puts the quality and availability of healthcare facilities at risk (AAMC 2019). To compensate for this shortage and to assess the possibilities of reducing physicians' workload with AI-based chatbots, there is a need for sensible use cases from the physicians' perspective. **Paper VI** enlarges the literature treating use cases from the patient perspective (e.g., Laumer et al. 2019; Oh et al. 2017) by providing nine new use cases for AI-based chatbots involving the physicians' view. The integration of chatbots into documentation, anamnesis, and diagnosis was rated especially promising, identifying the anamnesis-diagnosis-treatment-documentation process as high potential use case for AI-based chatbots in healthcare, as described in Figure 12.

Contributions to AI Resistance Research in Healthcare. Existing research has effectively addressed physicians' reluctance to embrace IS change in healthcare, emphasizing factors like distrust (Bhattacherjee and Hikmet 2007; Hsieh 2015; Mettler et al. 2017). **Paper VII** extends this research in three significant ways.

First, we delve into the patients' viewpoint, exploring their motivations and perceptions regarding healthcare changes, offering fresh insights distinct from the healthcare providers' perspective (Penman et al. 1984) and into the specific IS context of AI-based chatbots. Second, upon closer examination of the identified configurations, we find that the absence of loss aversion implies that resistance to chatbots is not rooted in a lack of potential benefits associated with AI implementation. Instead, anticipated regret and uncertainty costs across all identified configurations lead to substantial patient resistance. This finding suggests that patients are primarily concerned about unforeseen negative consequences associated with using AI-based chatbots, coupled with distrust in the performance of the AI-based chatbot in two out of three configurations. Thus, our research demonstrates that physicians and patients influence the diffusion of new information systems in healthcare, and resistance primarily stems from fears related to AI-based chatbots rather than a lack of perceived benefits. Third, our findings indicate that the reasons for resisting AI-based chatbots vary depending on the number of annual patient consultations. Interestingly, patients exhibiting a high frequency of configurations also demonstrate a predisposition to resist change. This inclination may be linked to the habit-forming nature of repeatedly undergoing medical history taking due to multiple consultations, a factor known to influence behavior in information system contexts (Polites and Karahanna 2012).

Contributions to AI Adoption Research in Healthcare. Paper VIII provides deeper insights into the adoption of AI in healthcare, particularly in adopting AI-based chatbots. These insights significantly advance AI adoption research in healthcare in several ways. Firstly, physicians must weigh various factors when deciding to adopt AI-based chatbots. These factors encompass personal considerations, patient impact, and potential consequences, influencing their willingness to adopt AI (Keeffe et al. 2005; Payton et al. 2011; Shaffer et al. 2013). Secondly, **Paper VIII** reveals that physicians simultaneously assess perceptions of the IS, such as usability and efficiency, alongside AI-specific factors. These AI-specific elements involve the AI's ability to interact with physicians and patients, encompassing complementary knowledge and its capacity to interpret data, including the explainability of AI-generated results. Thirdly, we present empirical evidence that these perceptions are processed as configurations, ultimately determining whether there is a high or low intention to adopt AI. Assessing the dominance of enablers and inhibitors within a specific configuration plays a pivotal role in this determination.

Our contributions to AI adoption research in healthcare can be summarized as follows: We systematically categorize and empirically validate considerations related to physicians, patients, and consequences, categorizing them as enablers and inhibitors. This operationalization includes AI-specific variables such as AI result explainability and complementary knowledge, enriching the existing knowledge on AI adoption in healthcare (e.g., Laumer et al. 2019). Further, we identify and analyze specific configurations that impact the intention to adopt AI. We elucidate which combinations of enablers and inhibitors (Cenfetelli and Schwarz 2011) lead to a high or low intention to adopt AI. We emphasize the significance of AI-specific perceptions, highlighting their crucial role in AI adoption within healthcare. Additionally, we shed light on assessing the dominance among individual enablers and inhibitors within a configuration, influencing a high intention to adopt AI. This understanding clarifies why certain configurations result in strong adoption intentions, even when inhibitors are often characterized as more influential than enablers, enriching IS research (Cenfetelli and Schwarz 2011). Our study reveals that the intention to adopt AI hinges on which enablers and inhibitors are deemed dominant, underlining the ethical responsibility of physicians towards their patients as a driving force.

Leveraging these contributions enhances our capacity to elucidate, predict, and address challenges related to AI adoption in healthcare. **Paper IX** enriches these findings with concrete recommendations for implementing AI-based chatbots successfully in hospitals. Ultimately, combining these insights facilitates the successful integration of AI technologies into healthcare beyond existing findings (Denecke et al. 2018).

5.1.3 Methodological Contributions: Mixed-Methods Research in IS

Paper X offers a twofold contribution to IS research, focusing on mixed-methods research (Venkatesh et al. 2013; Venkatesh et al. 2016). Firstly, we introduce three core concepts that capture the essence of mixed-methods research and its significance in the IS domain. These concepts should inspire and guide future authors, emphasizing the benefits of incorporating mixed-methods approaches. We provide detailed implementation guidelines (see Figure 17). Secondly, we conduct quantitative analyses of selected papers, offering insights into the evolution of mixed-methods studies in IS research while considering existing guidelines.

Additionally, we present a structured overview of mixed-methods research in the IS field, providing a foundation for future research. This structured representation aims to guide upcoming studies and highlight exemplary research using mixed-methods approaches. **Papers**

XI and XII are among these examples and enrich existing guidelines by including configurational approaches in mixed-methods studies.

5.2 Practical Implications

This section outlines the practical implications gathered in this dissertation. As such, the **Introductory Paper** provides practical recommendations on navigating the dual nature of IS and making IS part of the solution to health system overload, minimizing the burdening while unleashing the supporting effects. We structure the practical implications deduced from our twelve research papers accordingly into practical implications preventing the burdening effects of IS use, unleashing the supporting effects of IS use, and conducting mixed-methods research.

5.2.1 Practical Implications: Minimizing the Burdening Effects of IS Use

Raise Awareness of IS-Enabled Advertising Stress among Individuals, Advertisers, and Publishers. Reducing the burdening effects of IS-enabled advertising requires the involvement of the whole advertising value chain, including the advertiser, so the company issuing the ad, the publisher, for example, app developers displaying the ad, and the individual exposed to the ad (Müller 2019). Advertisers should select less-invasive ad formats, publishers should use natural usage pauses to cause fewer interruptions, and individuals who are easily impressed by influencer marketing or suffer from other mental health conditions must consume social media and other apps very mindfully (**Papers I to III**).

Aim for a Better Integration of Remote Workers. Many remote work stressors arise from social isolation and the perceived lack of organizational support. We recommend that organizations take proactive steps to address remote work communication issues. Many employees seek clear guidelines on using specific communication tools and best practices for remote work communication. These guidelines should encompass the use of video during remote meetings and calls to maintain a sense of face-to-face interaction, the promotion of regular coffee chats or informal sessions among employees and supervisors to foster social connections, the implementation of adequate feedback mechanisms to ensure that employees receive guidance and support and the incorporation of social elements into remote communication that cannot be conveyed through video or written channels.

Additionally, organizations should actively support employees in their transition to remote work by providing necessary equipment and offering guidance on stress reduction techniques. This guidance may include advice on taking regular breaks, combating isolation, building self-discipline, and enhancing resilience.

Furthermore, organizations should consider leveraging the capabilities of IS to motivate remote employees. Given the challenges of remote work, traditional means of rewarding employees, such as ordering pizza or providing office perks, may not be feasible. Instead, organizations can explore alternative methods, such as using digital nudging to encourage employees to engage with their team members and stay connected, fostering organization-wide virtual events, such as charity runs or walks, where employees can participate as teams, providing vouchers for video-on-demand or audiobook platforms to help employees and their families stay engaged during remote work or delivering fruit and vegetable boxes to employees to promote their well-being. These practical recommendations can help organizations address the challenges of remote work and enhance employees' well-being and commitment in a virtual work environment (**Paper IV**).

Provide a Portfolio of Mitigations for Employees to Choose from. Mitigating technostress is a multifaceted challenge with potential unintended consequences. As such, organizations need to recognize that reducing technostress is a complex endeavor. Technological mitigation measures alone are insufficient without considering cultural and social aspects. Effective mitigation measures require a robust technology infrastructure, a strong team culture, and socially adept leadership. It is essential to understand that mitigating technostress is a long-term commitment rather than a quick fix. Employees' individual working habits and preferences can influence their perception of mitigation measures, potentially viewing them as restrictive. Organizations should adopt a comprehensive, holistic approach instead of a simplistic, one-size-fits-all solution. For example, organizations must educate employees on how to use these tools effectively to reduce technostress. Measures aimed at mitigating technostress related to internal communication should establish best practices for choosing appropriate communication tools, enhance employees' social awareness about communication timing and methods, and provide guidelines for accessing information from internal resources rather than relying on colleagues. Prioritizing social and cultural measures is essential to foster a shared mindset for technostress mitigation and prevent unintended negative consequences of implemented measures. While mitigation measures may not equally alleviate technostress for all employees, they still appreciate organizational efforts to reduce technostress by implementing such measures. Prioritizing employees' mental well-being demonstrates management's concern and appreciation for their work, ultimately increasing job satisfaction. We encourage organizations to actively involve employees in introducing technostress mitigation measures and listen to their needs to safeguard their well-being while maintaining productivity and job satisfaction (**Paper V**).

5.2.2 Practical Implications: Unleashing the Supporting Effects of IS Use

Paper VI identifies the anamnesis-diagnosis-treatment-documentation process as the most promising use case for AI implementation. As this implementation requires significant changes, hospitals and healthcare providers should prepare their staff for technological innovation through chatbots to increase potential acceptance and leverage the associated benefits.

To Reduce Patient Resistance, Focus on Concerns about the Unforeseen Negative Consequences of Utilizing AI-based Chatbots, not Benefit Spotting. Patients are concerned about potential regrets when using an AI-based chatbot in the future. To address this anticipated regret, healthcare facilities must proactively work on building trust, a task that demands substantial effort. One approach to bolstering trust is enhancing the explainability of the AI-based chatbot and its action by ensuring that patients clearly understand what the chatbot is doing and can anticipate the consequences of its integration into their healthcare journey. Transparency and clarity about the AI-based chatbot's role can also help alleviate concerns. Another strategy is to openly communicate the limitations of the AI-based chatbot in terms of performed tasks. Positioning it as a supportive tool for physicians that expedites and improves data collection without competing for precious patient-physician interaction time can reassure patients. Further, we recommend that hospitals do not solely focus on showcasing rational benefits. Resistance does not stem from a lack of perceived advantages but rather from patients' apprehensions and fears associated with the AI-based chatbot. One potential solution is introducing a testing version of the chatbot, allowing patients to gain firsthand experience and refine their assessment of its capabilities. This iterative approach can help alleviate concerns and foster patient acceptance (**Paper VII**).

Consult Recommendations for the Implementation of AI-based Chatbots before Starting. For healthcare providers and hospitals contemplating the adoption of AI-based chatbots, **Papers VIII and IX** offer strategies to promote early AI adoption, even during the pre-implementation phase of AI-based chatbots. Hospitals must prioritize understanding and addressing physicians' perceptions and thoughts, as these factors influence their intention to adopt AI. Changes in how physicians work can induce cognitive and emotional resistance, potentially resulting in the unsuccessful implementation of AI-based chatbots. Hospitals should consider several strategies to address this resistance and avoid AI implementation setbacks. Firstly, starting with a trial version of the AI application is advisable. During this phase, hospitals can transparently communicate the AI system's capabilities and limitations, helping foster realistic expectations among physicians and staff. Secondly, we reveal that physicians place considerable emphasis on AI-specific perceptions related to the quality and safety of patient treatment, such as trust, complementary knowledge, and explainable AI results, when deciding to adopt an AI-based chatbot. Therefore, the involvement of domain experts in training the AI-based chatbots is crucial. Hiring professionals with expertise in the relevant field can provide valuable support for machine learning processes and ensure that AI integration aligns with the specific needs of healthcare professionals. Thirdly, we recommend the incremental implementation of AI. Hospitals should introduce AI solutions one step at a time, allowing physicians and staff to adapt gradually and become comfortable with the new technology. Lastly, maintaining open and transparent communication about the intended impacts of AI is essential. This ongoing dialogue can help address concerns, clarify objectives, and build trust among healthcare professionals, ultimately increasing the likelihood of successful AI adoption.

5.2.3 Practical Implications: Conducting Mixed-Methods Research in IS

Our provided guidelines (**Paper X**) and provided examples (**Papers XI and XII**) should encourage and support authors who may conduct more mixed-methods research in the future, leveraging the benefits of stressing their assets. Further, the guidelines and analysis of the status quo of mixed-methods research are valuable for review boards evaluating submitted mixed-methods work. Considering our analysis and the ongoing discussion on research guidelines (Siponen et al. 2021), we encourage reviewers to not only recommend guideline adherence but also assist authors in optimizing their mixed-methods studies to emphasize their strengths. The core concepts and insights we present can serve as a framework for evaluating future mixed-methods studies, accommodating valuable research that may not strictly adhere to all guidelines. Our portrayal of the current landscape underscores that while authors do not need to apply all core concepts, acknowledging and considering their impact can enhance paper quality and emphasize their contributions to IS research.

5.3 Limitations

Like any research endeavor, the results of this dissertation are constrained by limitations imposed by the chosen methodologies and frameworks.

Firstly, our research faces sampling limitations in terms of constrained generalizability. When examining the burdening effects of IS use, we did not control for cross-platform usage or other stressful influences besides exposure to advertising (**Papers I and II**). Further, we only considered a sample of users who received advertising and actively looked at it, which leaves individuals showing ad avoidance aside. This limitation affects our results because we only consider problem-focused and not emotion-focused coping strategies (**Papers I to III**). Also, we did not control for any existing mental health condition contributing to the reduced well-being (**Papers I, II, IV, and V**). Additionally, we recognize that there might be context specificities concerning our samples. For example, IT professionals have a higher computer self-efficacy, which might contribute to the dominance of techno-overload and techno-invasion, causing technostress in **Paper V** instead of other identified techno-stressors (Ragu-Nathan et al. 2008). Further, physicians and patients cannot fully assess AI-based chatbots' technological readiness and capabilities, leading to unrealistic expectations (**Papers VI-IX**). Also, sampling individuals from one cultural context might have shaped their attitude to remote work (**Paper IV**) or AI-based chatbots (**Papers VI-IX**).

Secondly, our research faces limitations concerning the data collection. We restricted our literature review to the AIS Scholarly Basket of Eight and only had restricted access to companies and hospitals, leading to limitations in the generalizability of the results (**Papers IV, V, VII, IX, X, and XII**). Although prior research has proven that one case can deliver reliable results in investigating specific phenomena (Collins and Smith 2006), different hospitals or companies might have different cultures or prior experiences. Further, in **Papers V and IX**, we collected data from the retrospective, which can influence the reports (Lee 2006). The same applies to the voluntary nature needed to complete the questionnaires in **Papers VIII and IX**, which might have biased the answers in terms of sample selection (Hu et al. 2017), as only those who are extremely in favor of the AI-based chatbot or extremely against it might have taken their spare time to answer the survey. This could be one reason we do not see more variance in the configurations yielding a low intention to adopt AI. Additionally, we only collected data at one point in time. This especially affects those papers treating coping responses (**Paper II**) or intention instead of behavior (**Papers II and VIII**). Although intention is considered a reliable predictor of actual behavior, it does not explain behavior (Polites et al. 2017), leading to an intention-behavior gap (Bhattacherjee and Sanford 2009). Further, those papers treating the pre-adoption phase of IS need to be based on indirect experiences and beliefs of current non-users. Even though direct experiences and beliefs could predict behavior better, deducing factors from indirect experiences is still valid, which is the only possibility to study in the pre-adoption phase (Karahanna et al. 1999). For some studies (**Papers III, VII, and XI**), we shared our questionnaires on crowdworking platforms to strive for a more diverse population, which required additional means to ensure high data quality (Lowry et al. 2016).

Lastly, we acknowledge limitations stemming from the applied data analysis approaches. The received qualitative inferences are subjective and limited to the specific samples (**Papers V, VI, and IX**). We compensated for this weakness in our mixed-methods approaches. Further, the presented QCA studies do not aim at reaching full coverage, so there might be configurations of variables left out, such that not every participant can be mirrored in one configuration. This is intended, as we aim for reliable and stable configurations in terms of coverage (**Papers II, III, VII, VIII, XI, and XII**).

5.4 Future Research

This dissertation contributes to the discussion of the role of IS use in health system overload by identifying strategies to minimize their burdening effects while unleashing the supporting effects. We deduce two major avenues for future research from the identified results and contributions.

IS Use a Remedy to Burdening IS Use Effects. So far, this dissertation has established IS use as a potential source of lower well-being and burden to mental health. This perspective has left promising facets aside. First, **Paper XI** and recent literature have begun exploring the potential positive effects of stress when stressors are perceived as challenges (Califf et al. 2020). However, although we identified different stress reactions to IS use, we have not considered the actual appraisal of these reactions regarding challenge or hindrance stress. Future research could delve into potential strategies to foster challenging aspects of stress. This might involve investigating communication strategies that foster positive Eustress, such as gamification approaches that monitor social media use and challenge the user to think positively or laugh about stressful events to grow and overcome them. Such initiatives provide a more comprehensive understanding of stress, burdening mental health, and its implications. The involvement of IS use does not have to end with positively influencing the appraisal of stressful events but could actively support mitigation strategies. **Paper V** identified a trifecta of technological, cultural, and social mitigation strategies. While simple functionalities and nudging allow technological mitigations to stress, supporting the other two types of mitigations is more complicated. AI-based chatbots can potentially be harnessed to support cultural and social mitigation strategies. For example, future research could examine how virtual realities can function as suggestion boxes, gathering employees' stressful experiences and developing strategies to solve them. Further, they could interpret working style, language, and tone to deduce the actual stress level of employees and suggest breaks or just listen to them. Given the anticipated significance of cultural and social mitigation aspects in what has been referred to as the 'feeling economy' (Huang et al. 2019), describing the rising importance of soft skills and social features for successful performances, to understand how IS, particularly AI, can be used as mitigation, up to designing stress-free IS use, is crucial and depicts a promising avenue to future research, working on the following research question: *How can we make IS use a remedy to burdening IS use effects and what are potential pathways to stress-free IS use?*

Effectiveness and Downsides of Using AI to Unburden Health Workforce. Concerning the understanding and unleashing of supporting effects, this dissertation delivers sensible use cases and examinations of user behavior to outline successful pathways to implementing AI-based chatbots in healthcare. However, these considerations describe prospected benefits in the pre-adoption phase (Karahanna et al. 1999). Without a broader implementation of AI in sensible use cases in healthcare, we can neither assess the effectiveness of these means in reducing health system overload nor the potential downsides of using AI in terms of burdening effects. When we have reached a satisfactory level of AI diffusion in healthcare, future research could re-evaluate AI use. Concerning the effectiveness, one promising future research opportunity would be to draw from the identified AI-specific characteristics influencing a successful implementation, particularly concerning the ability to interact with users and interpret data, and delve deeper into these perceptions, potentially examining their non-linear nature. For instance, prior research has demonstrated that anthropomorphic traits can enhance acceptance, but only up to a certain point. Beyond that threshold, these anthropomorphic characteristics can become unsettling, known as the 'uncanny valley' (Burleigh et al. 2013). A similar effect might apply to the belief in AI's superiority, conflicting with the idea of AI as a valuable colleague or the explainability of AI. Exploring various levels of these perceptions, for instance, by asking when an AI system is considered "explainable enough" and whether we can attain this level through automated solutions, is important. Concerning possible downsides of AI use, we know, and emphasized in Chapter 1 of this dissertation, that IS also has the power to stress employees, e.g., through the fear of being replaced by IS or by feeling uncertain dealing with it (Maier et al. 2019). Based on that stream of research, it might be valuable to understand the trade-off between negative and positive effects grounded in AI implementations, especially when delegating tasks to virtual entities. This raises the following research question for future research: *How can we measure the effectiveness of AI implementations in unburdening health workforce, and what are the possible downsides of using AI in healthcare?*

Both of the identified research avenues continue our efforts in making IS use a part of solving health system overload.

6 CONCLUSION

Health system overload is a pressing issue faced by numerous countries worldwide, which occurs when the existing healthcare resources cannot adequately address the demand. Exploring the dual nature of IS use in the context of health system overload, this dissertation comprises twelve research papers that contribute to the discourse on the role of IS. First, we provide deeper insights into the burdening effects of IS use, specifically focusing on IS-enabled advertising and remote work contexts. We propose measures to reduce and prevent these adverse effects. Then, we demonstrate how AI-based chatbots can support the health workforce, particularly physicians, during the anamnesis-diagnosis-treatment-documentation process. Emphasizing pertinent user behaviors, such as adoption and resistance, we offer recommendations to prevent AI implementation failures and promote adoption to realize the associated benefits. Lastly, we enhance our findings' methodological rigor and reliability, presenting concise guidelines for conducting mixed-methods approaches as utilized in this dissertation. Employing a methodologically robust dual approach that simultaneously mitigates burdening and harnesses supportive effects, we can conclude that we can recommend IS use to address health system overload, when it is closely monitored and successfully implemented.

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Chapter 1: IS Use and Mental Health

Paper I

Information Overload and Presented Lifestyle in Social Media:

A Stress-Perspective on the Effects on Mental Health

Lea Reis
University of Bamberg

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Paper II

In-App Advertising Stress and Coping Strategies:

A Mixed-Methods Study

Lea Reis
University of Bamberg

Christian Maier
LMU Munich School of Management, Ludwig-Maximilians-Universität München

Jens Mattke
University of Bamberg

Tim Weitzel
University of Bamberg

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In-App Advertising Stress and Coping Strategies: A Mixed-Methods Study

ABSTRACT

Companies evermore engage in in-app advertising (IAA) to reach customers, but app users receiving IAA are increasingly stressed, reducing advertising success. To explain this phenomenon, the transactional stress model guides our research to identify IAA stressors, strain, and coping strategies. We apply a complementary mixed-methods approach. We develop an IAA stress model from the literature and enrich it with qualitative interviews (N=26). To understand the selection of coping strategies, we apply qualitative comparative analysis (QCA) based on surveys (N= 205). Our results show that (1) IAA can evoke stress, (2) there are different combinations of IAA stressors yielding different coping strategies, (3) even when confronted with the same IAA stressors, app users select different coping strategies, depending on whether they want to oppose or escape IAA, and (4) IAA stressors can yield proactive coping. We contribute to advertising and stress research by applying a stress perspective to IAA and offering contextualized stressors, strain, and coping responses. Our results aim to increase awareness for IAA stress and its negative impact on advertising revenue. We provide recommendations: (1) Display in-app ads in natural usage pauses. (2) Carefully consider the content and voluntariness of engaging ads. (3) Choose silent ad formats for highly targeted in-app ads and display them at a low frequency. (4) Do not combine irritating random content with interrupting formats! With this research, we shed light on the potentially harmful consequences of IAA stress for app users, advertisers, and app developers.

Keywords: In-app advertising, mixed-methods, qualitative comparative analysis (QCA), IS-use-related stress, marketing stress, emotional exhaustion, discontinuance

1 INTRODUCTION

With 88% of smartphone usage time spent on mobile apps (BuildFire 2022), the in-app environment is ideal for advertisers to reach potential customers (Kovalenko 2022). Mobile apps are closely connected to users' personal lives and daily habits and enable effective and individual advertising within the app, called in-app advertising (IAA), through better targeting (Kovalenko 2022). The higher relevance of in-app ads for app users results in click-through rates twice as high as those of mobile web ads (Desaulnier 2017) and the increasing popularity of IAA among advertisers and app developers. While IAA seems to be in the best interest of app users, developers, and advertisers, app users do not always perceive IAA as beneficial and increasingly complain about it. The latest research (Gao et al. 2022) shows that app users are overwhelmed with the amount and frequency of in-app ads, annoyed by the non-skippability and interruption, and frustrated with their app usage experience. Consequently, two out of three app users considered, at least once, uninstalling the app and escaping the intrusive and exhausting in-app environment (Gao et al. 2022).

One possible explanation for the reported negative emotions associated with received in-app ads and the wish to escape them by quitting the app could be the stress caused by IAA. Theoretically, stress is a transactional process, where stressors transact into strain, so adverse psychological or emotional reactions (Lazarus and Folkman 1984). This translation happens when individuals assess stressful situations, such as exposure to IAA, as too demanding and potentially harmful, which yield coping strategies to deal with or escape the stressful situation (Lazarus and Folkman 1984). Research in other areas involving information technology (IT) indicates that factors like interruptions (Chen and Karahanna 2018), negative emotions (Maier et al. 2012), and information overload (Maier et al. 2015a) indeed either cause or intensify the stress perceived by users. In the extreme, those works also show that discontinuing the usage of the specific IT or IT service can be one possible reaction to escape a stressful environment (Maier et al. 2015b). Whether IAA causes or contributes to app users' stress has not yet been sufficiently revealed in existing advertising or stress research. If IAA actually stresses app users, this would not only evoke adverse health outcomes on the app users' side (Crawford et al. 2010) but also impose challenges for advertisers and app developers.

First, advertising research indicates that stressed consumers are less likely to purchase the advertised products (Albrecht et al. 2017). So, if app users are stressed, IAA could not yield the desired effect of generating sales. Second, and even worse, research on mobile web advertising shows that the users associate their negative advertising experiences with the advertisers, damaging their brand image in the long run (Han et al. 2014). Consequently, IAA's remarkably high recall rates (Kaplan 2019)could turn into a disadvantage if the recall is negatively connoted. Third, as a possible reaction to perceived stress is to escape the stressful environment (Maier et al. 2015b), app users might uninstall the app and report their negative experiences (Gao et al. 2022). Both reactions negatively affect user retention rates and reduce the potential advertising base, eventually reducing ad revenue for advertisers and app developers.

In light of the rising popularity of IAA and the potentially harmful consequences of IAA stress for app users, advertisers, and app developers, this study aims to understand whether IAA actually stresses app users, what contributes to that stress, and how users respond to it. To answer those questions, we take the app users' perspective and identify IAA stressors, IAA strain, and coping strategies from existing literature. Then, we enrich those findings with results from an interview-based study (N=26). We reveal four IAA stressors and one psychological strain, namely emotional exhaustion, yielding two problem-focused coping strategies to deal with or escape the stressful environment. To better understand how the identified stressors jointly contribute to the *discontinuance of mobile app usage* and *offline mobile app usage* and to discover differences in yielding the two coping strategies, we used a qualitative comparative analysis (QCA) based on quantitative surveys (N=205). Our results indicate that (1) IAA can evoke stress that yields coping strategies, (2) there are different combinations of IAA stressors yielding different coping strategies, (3) even when confronted with the same combinations of IAA stressors, app users select different coping strategies, depending on whether they want to oppose or escape IAA, and (4) IAA stressors can yield proactive coping responses. Based on those insights, we deduce practical recommendations for advertisers and app developers on reducing IAA stress for app users. We contribute to advertising research by offering a stress perspective explaining the adverse effects of IAA on app users. Further, we contribute to stress research by showing contextualized results identifying IAA stressors, strains, and problem-focused coping strategies.

2 THEORETICAL BACKGROUND

To understand the stress potential of in-app advertising (IAA), we first present related literature treating app users' perceptions of IAA. Then, we will outline the stress-theoretic lens used in this study and finally use this lens to identify indications for IAA stress in the existing literature.

2.1 App Users' Perceptions of In-App Advertising

In-app advertising (IAA) refers to ads or marketing messages delivered within mobile applications on various mobile devices, such as smartphones or tablets (Kovalenko 2022). The in-app environment offers multiple benefits to advertisers. Those benefits include a broad advertising base due to the high usage times of apps, fewer possibilities to block ads, and more effective and personal targeting due to a precise picture of app users' interests and habits (Rafieian and Yoganarasimhan 2021). The better targeting converts into higher click-through and conversion rates, promising higher ad revenue for advertisers and app developers (Desaulnier 2017) and more relevant and valuable ads for the app users (Mattke et al. 2021a). In the same vein, the latest research reveals that IAA can lower the app's user experience when users perceive IAA as intrusive, annoying, or causing performance costs (Gao et al. 2021; Gao et al. 2022; Ghose and Han 2014). Among others, app users report developing negative emotions when in-app ads are irrelevant, come at a high frequency, are not skippable, interrupt the app usage, or require interaction (Gao et al. 2022). Further, app users worry about in-app ads invading their privacy due to the context information used with in-app ads, such as user preferences or locations (Rafieian and Yoganarasimhan 2021).

Prior stress research identifies the perception of negative emotions while using mobile apps (Ardèvol-Abreu et al. 2022) and avoiding stressful situations through discontinuance as stress components (Maier et al. 2015b). Those works identify app features, such as overload from social media requests (Maier et al. 2015a), as sources of this experienced stress. Whether IAA, which does not count as an app feature, also causes or contributes to app users' stress has not yet been considered, despite indications in practice that this might be the case (McGrath 2019). We next outline related research treating stress in general and advertising to offer that perspective.

2.2 Related Research on Stress

In general, stress arises when an individual perceives a discrepancy between the demands of a situation and their ability or resources to deal with it (Folkman 1984). Thereby, stress is understood as a transactional process that translates demanding stimuli, perceptions, or situations, called stressors, into adverse emotional or psychological reactions, called strain (Lazarus and Folkman 1984). When confronted with stressors and perceiving strain, individuals respond with coping, a function of behavioral, cognitional, and perceptual efforts to handle, reduce, or tolerate the threatening demand (Folkman 1984). So, coping refers solely to the taken efforts, independent of their success in lowering strain (Latack and Havlovic 1992). Coping can either be reactive, when individuals already perceive strain, or proactive, in response to stressors to avoid strain. To select a coping strategy, individuals undergo a cognitive appraisal process, consisting of primary and secondary appraisal, to first estimate the threat of the demand and then assess their ability to handle it (Skinner et al. 2003). Numerous coping strategies exist, which can be cross-classified into different categories of focus and methods of coping (Latack and Havlovic 1992; Skinner et al. 2003). One possible classification of the focus is the problem-emotion distinction, where problem-focused strategies aim at addressing or solving the problems related to the stressful situation, and emotion-focused strategies primarily manage or regulate emotions arising from the stressful situations (Folkman 1984). Individuals increasingly decide for problem-focused coping when they perceive their situation as changeable and for emotion-focused coping when they perceive their situation as unchangeable (Folkman 1984). With the set focus of coping, we can distinguish between methods of coping, classified as control versus escape coping methods (Latack and Havlovic 1992). Control strategies implement a proactive, take-charge approach, whereas escape strategies consist of staying physically or emotionally clear of the stressful situation. The control approach differs conceptually from the escapist method, but both can focus on the problem or the emotion in stressful situations (Latack and Havlovic 1992).

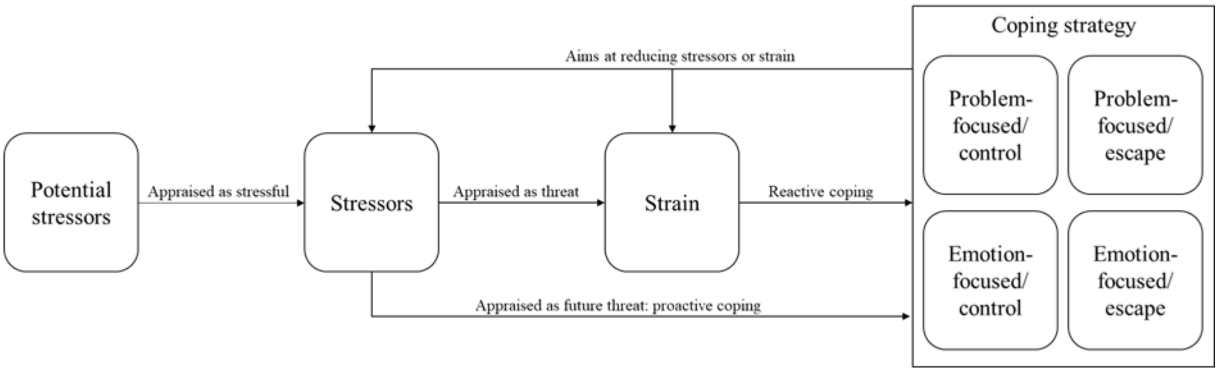

Figure 1. Coping Theory and the Selection of Strategies (Adapted from Lazarus and Folkman (1984))

2.3 Towards an Understanding of In-App Advertising Stress

While existing advertising or stress literature has not yet touched on IAA stress, there are practical indications that users have shown stress symptoms when dealing with IAA (McGrath 2019). Furthermore, advertising literature illustrates app users' negative perceptions of IAA: They perceive IAA as intrusive due to a high frequency and undesired interaction, as interruptive, invading their privacy, evoking performance costs, and irritating. Those perceptions cause negative emotions, such as annoyance and frustration, resulting in feeling overwhelmed and exhausted (Gao et al. 2021; Gao et al. 2022; Rafieian and Yoganarasimhan 2021). Based on prior considerations in other contexts (Boswell et al. 2004; Tarafdar et al. 2010), we can classify app users' negative perceptions of IAA as potential stressors since they evoke strong emotional responses to IAA. However, which potential stressors are appraised as stressful and can be considered IAA stressors remains unexamined. Further, literature considers overwhelming emotional reactions resulting in emotional exhaustion a psychological strain

(LePine et al. 2004; Maier et al. 2012) that yields reactive coping (Weinert et al. 2019). Based on the reported findings in advertising literature (Gao et al. 2022), this strain could also apply to IAA stress.

Concerning coping strategies, based on the understanding of classifications, problem-focused strategies in tackling IAA stress concentrate on reducing or stopping the confrontation with in-app ads. In contrast, emotion-focused strategies focus on being less emotionally affected by them. Prior literature reports app users' considerations of uninstalling apps as a reaction to the evoked negative perceptions (Gao et al. 2022). Leveraging insights from literature in the IT stress domain (Califf 2022; Maier et al. 2015b), the discontinuance of app usage can be considered a coping strategy. However, while we can classify discontinuance as a problem-focused coping strategy, the method remains unclear since the literature does not indicate whether app users use this strategy to regain control or escape from IAA.

Additionally, there is a whole literature stream on ad avoidance (e.g., Cho and Cheon 2004) that, from what we have learned from stress literature (Folkman 1984; Latack and Havlovic 1992), could be considered an emotion-focused coping strategy for advertising stress. While ad avoidance diminishes the advertising effectiveness, it does not necessarily reduce the potential advertising base and does not influence the delivery or display of in-app ads, as app users do not actively look at or engage with the ads. Therefore, in the further course of this study, we primarily focus on problem-focused coping strategies.

In summary, the literature provides us with a set of potential IAA stressors (interruption, privacy invasion, irritation, high costs, intrusiveness, and undesired interaction), one psychological strain (emotional exhaustion), and one problem-focused coping strategy (quitting mobile app usage). To better understand which of the identified perceptions can be considered IAA stressors, how these stressors contribute to emotional exhaustion, and how they yield problem-focused coping strategies, we apply a complementary mixed-methods approach (Reis et al. 2022; Venkatesh et al. 2013) and proceed in two steps. First, we refine our model with a qualitative interview study (Myers and Newman 2007; Schultze and Avital 2011), selecting actual IAA stressors from the perceptions presented in the literature and identifying problem-focused coping strategies. Second, as prior research indicates that stressors do not have individual but combined effects (Khedhaouria and Cucchi 2019) we use qualitative comparative analysis (QCA) based on surveys to reveal how combinations of the identified stressors yield different coping strategies.

3 REFINEMENT OF THE RESEARCH MODEL

To enrich the information gathered from existing literature, we conducted 26 semi-structured interviews, refining our research model.

3.1 Interview Procedure

Data collection and sampling strategy. We followed a non-probability sampling strategy to identify app users who receive IAA to be aware of the benefits and demands that come with it. We present the demographics in Table 1. The interviews took about 20 minutes each. We recorded the interviews anonymously and transcribed them with the permission of each participant. We interviewed all participants virtually. After we asked them about their general perception of IAA and whether they have experienced stress when confronted with it, we asked them about IAA stressors and coping strategies. We further used the interviews to validate the insights from existing literature. We present a complete guideline in Appendix A.

Biological sex in percent		**Age in percent** (Mean: 32.46; SD: 10.34)		**Average app usage time in percent**	
Male	53.85	≤20	11.54	≤1 hour	3.85
Female	46.15	21-30	15.38	1 – 1.5 hours	7.69
Other	0.00	31-40	30.77	1.5 – 2 hours	15.38
		41-50	26.92	2 - 3 hours	30.77
		51-60	11.54	3 - 4 hours	30.77
		>60	3.85	4 – 5 hours	7.69
				>5 hours	3.85

Table 1. Demographics Study 1 (N=26)

Data Analysis. We coded all interviews following Myers' (2019) descriptive and interpretative coding scheme. First, we identified the statements describing IAA stressors and coping strategies. Then, we grouped similar statements using descriptive and interpretative coding and categorized them into IAA stressors and strain. We present a coding example in Appendix B.

Validation. We designed the study following the insights gained from prior research. The selected sample is appropriate and large enough since the reasonable sample size for phenomenological interviews is ten participants (Collins et al. 2006). We gathered data from app users regularly confronted with IAA. While conducting the interviews, we were sensitive to flexibility, nondirection, specificity, and range (Sarker et al. 2018). We recorded and transcribed the interviews and used coding approaches recommended in the literature (Myers 2019). We did this analysis iteratively with co-authors and compared our results constantly. We reached interrater reliability of 0.93 regarding reliability and plausibility (Feng 2014; Fleiss et al. 1981).

3.2 Interview Results: The In-App Advertising Stress Model

Concerning IAA stressors, our interviews confirmed four of the perceptions reported in prior research as IAA stressors, namely interruption, irritation, privacy invasion, and undesired interaction, but did not reveal additional ones. While interruption and undesired interaction primarily address the format and display of the in-app ad, irritation, and privacy invasion relate to the content. We will define the identified IAA stressors in the following.

Interruption. Interviewees reported that they perceive the frequent interruption by in-app ads as stressful since interruptions hinder them from using the actual function of the app. In line with prior research (Chen and Karahanna 2018), we define the IAA stressor *interruption* as an advertising-related occurrence while using mobile apps that impedes or delays a user by breaking the continuity of ongoing activity in the non-advertising domain.

Irritation. Our interviews show that when app users perceive the content of in-app ads as irritating, they respond with strong emotions. In line with prior research (Aaker and Bruzzone 1985), we define the IAA stressor *irritation* as a feeling of uncertainty or disturbance in response to provocative, inappropriate, unfit, intrusive, and vulgar content of ads resulting in strong disapproval and annoyance.

Privacy invasion. While inappropriate content of in-app ads yields irritation, the other extreme causes severe privacy issues. In-app ads that fit too well because of exact targeting involving users' preferences, locations, and cross-platform information are perceived as creepy, intrusive, and harmfully invading users' privacy. In line with prior research (Rafieian and Yoganarasimhan 2021; Sutanto et al. 2013), we define the IAA stressor *privacy invasion* as in-app ads that compromise users' privacy with overly personalized content and targeting.

Undesired interaction. The interviews showed that app users perceive in-add formats that are non-skippable and require a certain amount of interaction(s) to continue with the actual function of the app as particularly stressful. Undesired interactions include display freezes, several closing attempts, and the obligation to click or to consume multi-media features. In line with prior research (Johnston et al. 2018; Yang et al. 2016), we define the IAA stressor undesired interaction as the need to perform unintended actions with the ad in the in-app environment to continue the ongoing activity.

Concerning IAA strain, the interviews identified one psychological strain resulting from the confrontation with IAA and the associated IAA stressors, namely emotional exhaustion, confirming prior considerations based on existing literature (e.g., Gao et al. 2022).

Emotional exhaustion. The interviews confirmed emotional exhaustion as a psychological strain in response to the identified IAA stressors. The reason for that is the constant arousal of negative and overwhelming emotions when confronted with the identified IAA, leading to an exhaustion of mental resources caused by excessive psychological and emotional demands (Fujimoto et al. 2016). In line with prior research (Ayyagari et al. 2011), we define the IAA strain *emotional exhaustion* as a chronic state of emotional and physical depletion resulting from exposure to strong and enduring emotions caused by IAA.

Concerning the problem-focused coping strategies, the interviews revealed two: one control strategy, namely offline mobile app usage, and one escape strategy, namely discontinuance of mobile app usage.

Offline mobile app usage. To deal with the experienced IAA stress, interviewees present the problem-focused strategy of offline mobile app usage. Interviewees report that to regain control over their app usage behavior and decisional autonomy of when to receive in-app ads, they consider switching off the Internet connection of the mobile device the app is running on. According to the interviewees, many apps still work and provide their fundamental functionalities offline, just without the delivery of IAA. The interviewees, who selected offline app usage as their coping strategy, all agreed that they refuse to sacrifice the free usage of the app for less confrontation with ads and that they are confident enough not to surrender themselves to the will of advertisers and app developers. They consider it their right to decide when they want to receive ads. Based on those insights and research in other domains (Jawade and Goyal 2018), we define the problem-focused control strategy of *offline app usage* as app users' intention to disconnect their devices from the Internet and use the mobile app offline in response to IAA.

Discontinuance of mobile app usage. Another problem-focused coping strategy depicts the discontinuance of mobile app usage. Interviewees report that they consider uninstalling the mobile app to escape the stressful exposure to IAA. While they regret sacrificing the app's functionality, they think it is a necessary step to escape from the stressful environment and agree that this environment is not changeable and forces them to flee. In line with prior research, we define the problem-focused control strategy of *discontinuance of mobile app usage* as app users' intention to quit using or uninstall the app in response to IAA.

Concerning the selection of coping strategies, our interviews indicate that app users do not perceive one particular IAA stressor in isolation but combinations of stressors. Those combinations lead to emotional exhaustion and IAA stress, eventually yielding the selection of coping strategies. The stressors varied between interviewees, meaning that interviewees selected the identified coping strategies for different reasons. To identify those combinations of IAA stressors and strain that yield the examined coping strategy, instead of individual effects, we need to consider the combined effects of IAA stress, so the interplay of IAA stressors and strain (see Figure 2), which we will outline next.

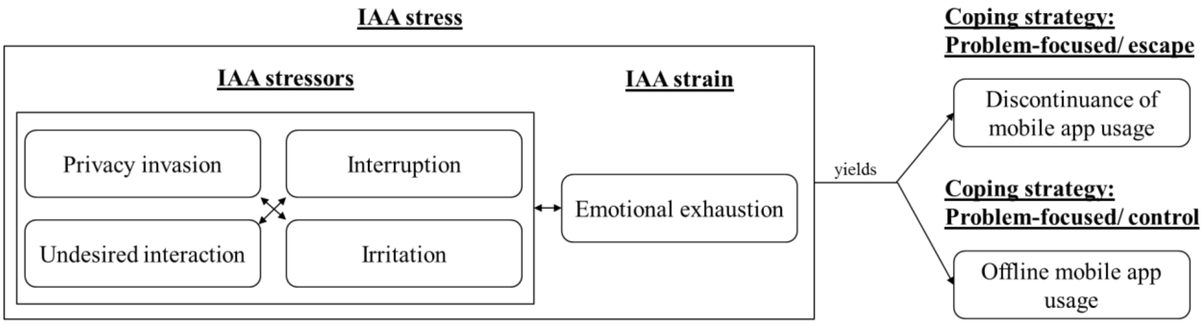

Figure 2. IAA Stress Model

4 COMBINED IN-APP ADVERTISING STRESS EFFECTS

To analyze the combined effects of IAA stressors and strain, yielding the selection of coping strategies, we based on a set-theoretic configurational approach (El Sawy et al. 2010; Misangyi et al. 2017) and used fuzzy-set qualitative comparative analysis (fsQCA) (Mattke et al. 2022; Ragin 2000). FsQCA is currently the dominant and most appropriate data analysis method for set-theoretic configurational approaches (Mattke et al. 2021b). It enables the analysis of sets of conditions, which we refer to as configurations, and their interplay with an outcome of interest (Pappas and Woodside 2021; Ragin 2014). In this study, conditions refer to the IAA stressors and strain, and the outcome of interest refers to the two identified coping strategies. fsQCA is increasingly prevalent across the business and behavioral sciences (e.g., Schmitt et al. 2017) and is gaining attraction in stress research (e.g., Maier et al. 2021; Pflügner et al. forthcoming), which is why we consider it suitable for this study.

4.1 fsQCA Procedure

Data collection and sampling strategy. We prepared an online survey. Our sampling strategy was to collect data from app users who were confronted with IAA and did not participate in our interviews. We shared the survey via social media platforms, which fits our sampling strategy to reach app users. Additionally, we ensured a high quality of the data by including two attention tests (Lowry et al. 2016), e.g., "Please select strongly disagree." In the first one, 57 users did not select the correct value on the Likert scale, and 24 participants failed the second attention test. The final sample consists of 205 data sets. We display demographics in Table 2.

Biological sex in percent		**Age in percent** (Mean: 36.13; SD: 11.55)		**Average app usage time in percent**	
Male	51.70	≤20	3.41	≤1 hour	0.49
Female	48.30	21-30	35.62	1 – 1.5 hours	11.22
Other	0.00	31-40	29.27	1.5 – 2 hours	17.56
		41-50	20.00	2 - 3 hours	25.85
		51-60	8.29	3 - 4 hours	19.02
		>60	3.41	4 – 5 hours	11.71
				>5 hours	14.15

Table 2. Demographics Surveys (N=205)

For the fsQCA method, the minimum required sample size to avoid finding random sufficient configurations for this study is 25, as the ratio of cases to conditions, here five, needs to be lower than 0.2 (Marx 2006; Marx et al. 2014). Therefore, we can say that we fulfill the sample size requirements in this study. This study relies on self-reported data, and even though the participants were unaware of the study's goal, we tested whether common method bias distorts our data. Our test results indicate that CMB is not an issue in this study (for more details, see Appendix C).

Measures and Measurement Model. Previous research validated and used our measures, which ensures content validity (see Appendix D). The loading of each item used in this study was higher than 0.707 (see Appendix D), attesting to indicator reliability (Carmines and Zeller 2008). We used a 7-Likert-scale with seven for "strongly agree" and one "strongly disagree".

The AVE of each construct was higher than 0.50, Cronbach's alpha 0.70, and the CR for each construct was higher than 0.70, attesting to construct reliability. We ensured discriminant validity as the square root of the AVE was higher than the corresponding correlations of the constructs (Fornell and Larcker 1981; Hulland 1999). Furthermore, we calculated the heterotrait-monotrait (HTMT) ratio of 0.75. This ratio is lower than the absolute HTMT$^{0.85}$ criterion (Henseler et al. 2014) and attests to discriminant validity. Those thresholds indicate that our measurement model is valid.

		Mean	*SD*	*AVE*	*CR*	*α*	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
(1)	*Interruption*	5.174	1.368	0.714	0.882	0.799	0.845						
(2)	*Irritation*	5.155	1.698	0.751	0.923	0.890	0.306	0.867					
(3)	*Privacy Invasion*	5.248	1.393	0.675	0.893	0.839	0.562	0.506	0.822				
(4)	*Undesired interaction*	4.671	1.732	0.779	0.934	0.905	0.332	-0.047	0.301	0.882			
(5)	*Emotional exhaustion*	4.324	1.846	0.837	0.954	0.935	0.259	0.451	0.457	0.371	0.915		
(6)	*Offline usage*	5.044	1.639	0.756	0.902	0.836	0.348	0.510	0.493	0.237	0.584	0.869	
(7)	*Discontinuous usage*	5.392	1.319	0.743	0.896	0.827	0.477	0.554	0.587	0.153	0.475	0.628	0.862

Note: The square root of AVE is listed on the diagonal of bivariate correlations; SD = standard deviation; α = Cronbach's alpha; AVE = average variance extracted; CR = composite reliability; SIC = single-item construct

Table 3. Descriptive Statistics and Discriminant Validity

Data Analysis. To analyze the configurations of conditions (IAA stressors and strain) that yield either offline mobile app usage or discontinuance of mobile app usage, we conducted two separate analyses, one for each coping strategy. Thereby, conditions and the outcome are represented as fuzzy sets to differentiate two extreme situations of set membership (Ragin 2000). A condition (e.g., privacy invasion) can be fully in a set, represented by the fuzzy set value of 1 (e.g., presence of privacy invasion), or can be fully out of a set, represented by a fuzzy value of 0 (e.g., absence of privacy invasion). All values between zero and one represent an individual membership in the set. For the data analysis, we used the QCA R package (Duşa 2018) and the fsQCA 3.0 software (Ragin et al. 2016). In both analyses, we proceeded in five steps.

We calibrated the survey data into fuzzy sets. Then, we analyzed for sufficient configurations. Sufficient configurations are only those that consistently yield a high discontinuance of mobile app usage or high offline app usage. In this study, a sufficient configuration is a configuration that exceeds a frequency threshold of three, a raw consistency threshold of 0.85, and a PRI threshold of 0.85 (Ragin 2009). We simplified the multiple sufficient configurations through logical minimization. Therefore, we can say that a condition in a sufficient configuration is either present (in the results displayed with ●) or absent (in the results displayed with ⊗), or present or absent, which refers to a 'don't care situation' (in the results displayed with blank space). For all configurations, we examined whether there are necessary conditions. A necessary condition always exists in configurations yielding a high, respectively, a low discontinuance of mobile app usage or a high, respectively, a low offline app usage. A necessary condition must exceed the consistency threshold of 0.90, the coverage threshold of 0.60, and the relevance of necessity threshold of 0.60 (Ragin 2006).

Validation. We tested the results for robustness and predictive validity. We assessed whether the results were stable if we used a lower or higher anchor for values fully in and out of a set. In line with recent QCA literature (Pappas and Woodside 2021), we also tested for the predictive validity of the QCA results, which means that we tried our QCA model on a test dataset that we did not use for developing the QCA model. We used the same data collection approach described above and sampled 102 participants for the test dataset. We then followed previous guidelines (Pappas and Woodside 2021) and analyzed the overall consistency of the QCA model on the test dataset.

4.2 fsQCA Results

Our analysis reveals three sufficient configurations for offline mobile app usage and five for discontinuance of mobile app usage.

Figure 3 shows that different subsets of the identified IAA stressors are relevant for yielding offline mobile app usage. Two out of three configurations show IAA stressors regarding the app's content, irritation, privacy invasion, and the structural factor of undesired interaction as present. App users perceive emotional exhaustion as IAA strain across all three configurations, which means that IAA stresses them.

	High outcome (Offline)			Low outcome (Offline)
	C1’	**C2’**	**C3’**	**C4’**
Interruption		⊗	●	⊗
Irritation	●	●		⊗
Privacy invasion	●		●	⊗
Undesired interaction		●	●	⊗
Emotional exhaustion	●	●	●	⊗
Raw coverage	0.65	0.17	0.56	0.31
Unique coverage	0.11	0.01	0.03	0.31
Consistency	0.95	0.97	0.95	0.94
Solution coverage		0.946		0.31
Solution consistency		0.700		0.94

Note: Black circles (●) indicate high perceptions, white crossed-out circles (⊗) indicate low perceptions and blank spaces ( ) indicate ‘don’t care situations.’ Black stars (★) indicate a necessary condition that needs to be high for a high outcome. We found no necessary condition.

Figure 3. QCA Results for Offline Mobile App Usage

Looking at the outcomes for discontinuance of mobile app usage (Figure 4), we see that the first three configurations map those yielding offline mobile app usage. The remaining two differ in that app users do not perceive emotional exhaustion, indicating that they do not perceive strain. Regarding the analysis of low outcomes, both datasets show that only if all stressors are absent, app users do not consider offline mobile app usage and discontinuance of mobile app usage as coping strategies.

	High outcome (DISC)					Low outcome (DISC)
	C1	C2	C3	C4	C5	C6
Interruption		⊗	●	●	●	⊗
Irritation	●	●		●	●	⊗
Privacy invasion	●		●		●	⊗
Undesired interaction		●	●	⊗		⊗
Emotional exhaustion	●	●	●	⊗	⊗	⊗
Raw coverage	0.60	0.15	0.51	0.23	0.72	0.45
Unique coverage	0.03	0.01	0.03	0.01	0.07	0.45
Consistency	0.97	0.98	0.98	0.97	0.97	0.94
Solution coverage	0.827					0.45
Solution consistency	0.963					0.94

Note: Black circles (●) indicate high perceptions, white crossed-out circles (⊗) indicate low perceptions, and blank spaces ( ) indicate 'Don't care situations.' Black stars (★) indicate a necessary condition that needs to be high for a high outcome. We found no necessary condition.

Figure 4. QCA Results for Discontinuance of Mobile App Usage

5 SELECTION OF COPING STRATEGIES

Combining the results of our interviews and the QCA analysis, we can deduce a clearer picture of whether app users perceive IAA stress and how they select an appropriate coping strategy to deal with the perceived demands.

Our interviews identified four IAA stressors that can translate into emotional exhaustion and yield either a problem-focused control strategy (offline mobile app usage) or a problem-focused escape strategy (discontinuance of mobile app usage). Our two QCA analyses confirm those findings, showing that each IAA stressor contributes to selecting coping strategies in different combinations. Further, all three configurations yielding offline mobile app usage and three out of five configurations yielding the discontinuance of mobile app usage identified emotional exhaustion contributing to this selection. This finding indicates that app users react adversely to present stressors and perceive strain. We, therefore, can conclude that IAA causes IAA stress.

Insight 1: Yes, IAA stresses app users.

Comparing the role of IAA stressors, we see that content-related IAA stressors (irritation and privacy invasion) contribute more often to selecting a coping strategy than format-related IAA stressors (interruption and undesired interaction).

Insight 2: Different content-related and format-related IAA stressors jointly yield problem-focused control or escape strategies.

Further, we see three overlapping configurations, indicating that app users perceiving the same combination of stressors select different coping strategies. Our interviews show that the underlying reason for choosing either control or escape strategies lies in app users' perception of decisional autonomy and their wish to escape or oppose IAA. Consequently, app users who do not want to deliver themselves to advertisers and are unwilling to sacrifice the mobile app's functionalities select a control approach. Weaker app users, who would even give up their apps to escape IAA, select an escape approach when facing the exact same stressors.

Insight 3: App users perceiving the same IAA stressors can still select different coping strategies depending on their willingness to oppose or escape IAA.

Interestingly, the analysis of app users' discontinuance of mobile app usage further reveals two configurations where app users do not show adverse reactions to the IAA stressors, so they do not perceive emotional exhaustion. This finding indicates that they select a coping strategy before even sensing stress. Prior literature confirms that individuals perceiving emotional exhaustion can only respond with reactive coping (Weinert et al. 2019). However, in some situations, individuals show proactive coping, meaning they select a coping strategy before stressors become a threat to protect themselves from adverse reactions (Weinert et al. 2019). While our interviews only showed reactive coping, the QCA results indicate that app users perform proactive coping and select to discontinue the mobile app usage because they wish to escape even the potential threat of perceiving emotional exhaustion.

Insight 4: IAA stressors can also yield proactive problem-focused escape strategies before an actual strain.

6 DISCUSSION

In light of the rising popularity of IAA and the potentially harmful consequences of IAA stress for app users, advertisers, and app developers (Gao et al. 2022), this study aims to understand whether IAA stresses app users, what contributes to that stress, and how users respond to it. Our results identify four IAA advertising stressors that cause emotional exhaustion among app users and several combinations of those stressors that yield two coping responses: offline mobile app usage and discontinuance of mobile app usage. With those results, we contribute to advertising and stress research by advancing the understanding of IAA stress. Further, we can deduce recommendations for advertisers and app developers to protect app users from IAA stress and eventually prevent a decline in their advertising base and revenue. We will outline those contributions and recommendations hereafter.

6.1 Theoretical Implications

This work provides contributions to advertising and stress research. We contribute to advertising research by applying a stress-theoretical lens to app users' adverse reactions to IAA advertising. While prior research has considered the influence of stress on advertising outcomes (e.g., Albrecht et al. 2017), we shed light on advertising as the source of stress and add a new sub-stream to advertising research treating the dark side of advertising effects. Specifically, using a stress theoretic lens helps us to distinguish between various negative perceptions of IAA in prior research (Gao et al. 2022) and four actual IAA stressors yielding coping responses, two addressing the content of the app (irritation and privacy invasion) and two addressing the format and display of the ad (interruption and undesired interaction). This distinction confirms considerations in prior research that structural and semantic factors of an ad jointly influence behavior in response to advertising (Mattke et al. 2021a) and contributes to the understanding of why app users uninstall their apps due to IAA.

Additionally, we identify emotional exhaustion as an IAA strain. While exhaustion has been a well-studied consequence in other advertising domains, such as consumer confusion (Walsh et al. 2007; Wang and Shukla 2013), we now trace the reaction back to overwhelming emotions in response to IAA stressors. This finding offers new explanations for that reaction and more mitigations regarding strain-reducing measures, such as practicing mindfulness (Pflügner et al. 2021).

Further, we identify two problem-focused coping strategies: offline mobile app usage and discontinuance of mobile app usage. While prior research has only observed the discontinuance of mobile app usage as an escapist approach to negative advertising experiences (Gao et al. 2022), we identify a new control approach with offline mobile app usage. Since both behaviors stem from different motivations, either to escape or to oppose the stressful situation, we must consider that even facing the same combination of stressors can still yield other behaviors. For some app users, the desire to escape is strong enough to use proactive coping and prevent them from perceiving IAA strain in terms of emotional exhaustion before it occurs.

We contribute to stress research by contextualizing coping theory and the transactional stress model within the advertising context (Lazarus and Folkman 1984). This contextualization adds IAA to known sources of stress and contributes to understanding the selection of coping strategies. Our results indicate that app users show proactive and reactive coping by selecting problem-focused control or escape strategies. This finding adds to considerations in prior research (Weinert et al. 2019) that coping strategies can result solely from the confrontation with stressors before even perceiving strain. Further, we understand that proactive coping can yield the same coping strategies as reactive coping but stems from different combinations of stressors. Identifying those combinations contributes to understanding how individuals select appropriate coping strategies and where to intervene or influence this selection.

Concerning research treating stress in response to IT usage, emotional exhaustion, and discontinuous usage intention have already been examined in other IT-use-related stress contexts (LePine et al. 2004; Maier et al. 2015a). However, these studies have established the relation between being stressed by certain features of that IT, e.g., social media, and developing the intention to discontinue the usage of this IT. Our research shows that IAA stresses app users, causes emotional exhaustion, and yields two coping strategies. Offline app usage confirms the analogy in the existing literature of wishing to end the confrontation with the actual stressor, so IAA. Discontinuance of mobile apps shows that app users consider quitting using the app, not only the exposure to IAA. This finding indicates a spillover effect of IAA stress on mobile app usage, meaning that IAA stressors affect users' reactions to IAA and contribute to behavioral changes in mobile device usage, with or without emotional exhaustion. For upcoming IT stress research, this means that they do not only have to consider app features as sources of stress but also services attached to the app, such as advertising, to explain the stress influence on user behaviors.

6.2 Practical Implications

Our results offer various recommendations for advertisers and app developers to reduce IAA stress for app users and keep their user base and ad revenue high. We show that coping responses result from combining format-related and content-related IAA stressors. For advertisers and ad developers, this means that either the ad's content or format should be stress-free. So when thinking about the ad design, one should ask themselves the following recommendations:

1.) Display in-app ads in natural usage pauses.

App developers should ask themselves whether the ad has to interrupt the flow of the app's functionality to create attention or if they can reach app users in natural pauses. If the interruption is unavoidable, the ad's content should at least be appropriate and fit the content or functionality of the ad. To avoid content-related stress, we recommend renouncing location-based or one-to-one advertising.

2.) Carefully consider the content and voluntariness of engaging ads.

Observations show that ads fostering user engagement are currently trending in the in-app advertising industry (Kovalenko 2022). Among others, playable ads generate high revenues as they provide a ‘safe’ test version to the app user. However, our results indicate that if the engagement with the ad is necessary to continue with the app’s functionality, app users perceive stress. If advertisers choose a voluntary design, the app users skip the ad at first. Still, there is also the chance that they will engage with the ad at a later point because it respects their decisional autonomy. If the design is not voluntary, advertisers should ensure that the selected content matches the functionality and domain of the ad.

3.) Choose silent ad formats for highly targeted in-app ads and display them at a low frequency.

Highly targeted ads displayed at a high frequency create the creepy feeling of being observed. Even though users might provide their data to get better matching ads, advertisers should not demonstrate their ability to target the user precisely in a too obvious way. Silent ad formats help reduce the targeted ad's offensiveness and intrusiveness. If users are not exposed to the ads too often, they might perceive them as a valuable source of information.

4.) Do not combine irritating random content with interrupting formats!

Inappropriate, vulgar, or embarrassing content combined with interrupting formats that disturb app users in their app usage can yield proactive coping strategies, leading app users to quit the app before even perceiving strain. While reactive responses require a certain chronic exposure to stress, with proactive coping, the reaction can come very quickly, diminishing the app user base and damaging the app’s reputation. Therefore, we advise app developers to select their advertisers carefully.

6.3 Limitations and Future Research

Our study is not limitation-free. We only considered a sample of users who received in-app advertising and actively looked at it, which leaves individuals showing ad avoidance aside. This limitation affects our results because we only consider problem-focused and not emotion-focused coping strategies. However, we believe examining emotion-focused coping in response to IAA is a valuable path forward, leaving this to future research. Further, since we only considered one point in time, we measured the intention to use the mobile app offline or to discontinue its usage. While our participants showed strong intentions, we cannot confirm that they performed the selected coping strategy (Bhattacherjee and Sanford 2009). However, if we had asked participants who had already completed the coping process, they would have had to report their experiences and perceptions from a retrospective, which would have influenced the reports (Lee 2006). So, we decided to collect actual experiences with IAA that confront participants right now and only measure their intention to perform a particular coping strategy.

Future research could enlarge our study and identify individual differences that influence the selection of coping strategies, as shown in other IS-use-related contexts. These individual differences include the consideration of personality traits (Maier et al. 2019), mindfulness (Thatcher et al. 2018), or the attitude toward advertising (Ducoffe 1996). Other sources of influence could be biases, such as digital nudging (Valta et al. 2022) or habituation effects (Weinert et al. 2015). Identifying those factors could help us better understand the selection of coping strategies and provide individual mitigations to IAA stress.

7 CONCLUSION

IAA stress has potentially harmful consequences for app users, advertisers, and developers. In this study, we use a stress-theoretic lens to uncover the stress potential of IAA, along with IAA stressors, strain, and coping strategies. Our results indicate that different combinations of stressors result in different proactive and reactive coping strategies. We contribute to advertising and stress research and offer recommendations for advertisers and app developers on reducing IAA stress and protecting their ad revenue.

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APPENDIX A: INTERVIEW GUIDELINE

We use the semi-structured interview guideline shown in Table 4 and conduct 26 interviews with individuals receiving IAA.

0 Demographic and screening questions
0.1 Do you use mobile apps on your mobile devices? What kind of apps? 0.2 How many hours do you use mobile apps every day? 0.3 Do you receive advertising while using mobile apps? 0.4 What do you think of in-app advertising in general?
1 In-app stressors, strain, and coping strategies
1.1 Do you perceive receiving in-app advertising as demanding? Why? 1.2 Do you feel interrupted/irritated/ your privacy invaded/ the need to interact/ high performing costs? 1.3 How do you feel after interacting with in-app advertising? 1.4 Would you describe the interaction with in-app advertising as stressful? 1.5 How do you react to those ads? What are your strategies for being less stressed? 1.6 Why/how do you select those strategies?
2 Closing
2.1 Is there room for improvement from the advertisers' or app developers' side? 2.2 Will you change anything in your behavior?

Table 4. Interview Guideline

APPENDIX B: CODING EXAMPLE

We use the interpretive/descriptive coding approach following Myers (2019). Table 5 shows the results of the three-step approach.

Data examples	Descriptive coding	Interpretive coding	Type	Classification
"If some ads pop up in the app, I am totally distracted in what I am doing and sometimes have difficulties finding my way back."	Mobile advertising distracts from current activity.	Interruption	Format-focused	In-app stressor
"I am very upset that ads just interrupt nearly every activity when using apps."	Mobile advertising cuts in on current activity.			
"I personally consider it my right to decide whether I want to receive ads or not, so I switch off the Internet. I understand that they [app developers] need to make money somehow, but I would be more open to it if it would be voluntary or just for a certain amount of time, and then for the rest of the month, I would receive no ads."	Decision autonomy	Offline mobile app usage	Control approach	Problem-focused coping strategy

Table 5. An Example of the Coding Procedure (Adapted from Myers (2019))

APPENDIX C: COMMON METHOD BIAS

In line with prior research (Podsakoff et al. 2003), we recognize that self-reported data could imply common method bias (CMB). We conducted two statistical analyses to identify the extent of CMB. First, Harman's single-factor test indicates whether the majority of the variance can be explained by one single factor. The examination reveals that only 38.15% can be explained by one factor. This value is below the 50% threshold (Podsakoff et al. 2003). Second, we added a CMB factor into the statistical analysis (Podsakoff et al. 2003; Williams et al. 2003) that contains every indicator of the original model. We transformed the remaining original factors into single-item constructs. Next, we compared the ratio of the coefficient of determination (R^2) with the CMB factor to R^2 without the CMB factor. As the method factor explains a delta of R^2 of 0.004 and the R^2 without this factor of 0.447 for discontinuance of mobile app usage and 0.432 for offline mobile app usage, we got a ratio of 1:111. Comparing this ratio with the percentages reported in prior research investigating CMB, we can state that CMB does not seem to influence our results significantly (Liang et al. 2017).

APPENDIX D: CONSTRUCTS AND MEASURES

In the following, we provide the constructs and measures of our survey. We measure all items on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree).

Classification	Type	Perception	Measurement item	Loading
IAA stressors	**Format-focused**	Interruption (adapted from Chen and Karahanna (2018))	In-app advertising interrupts me in my current activity more than I can handle.	0.793
			In-app advertising interrupts me in my current activity beyond my time available.	0.884
			In-app advertising changes my focus, which overwhelms me.	0.856
	Content-focused	Irritation (adapted from Aaker and Bruzzone (1985))	I perceive in-app ads as annoying.	0.908
			I perceive in-app ads as intrusive.	0.912
			In-app ads make me furious.	0.803
			In-app ads are a pain in the neck.	0.839
		Privacy invasion (adapted from Sutanto et al. (2013))	In-app advertising intervenes in my privacy.	0.800
			I feel spied on since I cannot retrace where personalized in-app advertising collects that nformation.	0.868
			In-app advertising using geographical data makes me feel uncomfortable.	0.801
			In-app advertising makes me feel constantly observed.	0.816
	Format-focused	Undesired interaction (adapted from Yang et al. (2016))	I interact with in-app advertising, though I would not do so voluntarily.	0.891
			I pay too much attention to non-skippable in-app advertising.	0.900
			I attach more relevance to in-app advertising than I would do voluntarily.	0.909
			I feel requested to act, react, or think because of in-app advertising.	0.899
IAA strain	**Psychological**	Emotional exhaustion (adapted from Ayyagari et al. (2011))	I feel exhausted using mobile browsers or apps.	0.916
			I feel tired of using mobile browsers or apps.	0.936
			I feel afflicted by using mobile browsers or apps.	0.919
			I feel bedeviled by using mobile browsers or apps.	0.888
Problem-focused coping strategy	**Control approach**	Offline mobile app usage intention (adapted from Jawade and Goyal (2018))	I will switch off my internet access to use apps without advertising.	0.904
			I am considering reducing the time spent watching in-app advertising by turning off the Internet on my mobile device.	0.903
			I will use the app offline to get rid of in-app advertising.	0.797
	Escape approach	Discontinuation intention of mobile app usage (adapted from Maier et al. (2015b))	I will uninstall the app to escape IAA.	0.788
			I will stop using mobile apps due to IAA.	0.919
			Due to IAA, I intend to pause the use of mobile apps occasionally.	0.757

Table 6. Constructs and Items

Paper III

A Mixed-Methods Study of Motivations in Mobile Ad-Blocker Use

Lea Reis
University of Bamberg

Christian Maier
LMU Munich School of Management, Ludwig-Maximilians-Universität München

Jens Mattke
University of Bamberg

Tim Weitzel
University of Bamberg

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A Mixed-Methods Study of Motivations in Mobile Ad-Blocker Use

ABSTRACT

Ad-blocker installations on mobile devices are rising quickly, jeopardizing advertising-based business models. However, the underlying motivation remains unclear, giving organizations no opportunity to change that. Grounding in motivation theory, this study theorizes that intrinsic motivation, extrinsic motivation, and amotivation influence individual intention to use mobile ad-blockers. We apply a two-strand mixed-methods approach consisting of one interview study and one qualitative comparative analysis (QCA). In Study 1, we base on interviews with non-mobile ad-blocker users to reveal seven core-contributing motivations. In Study 2, we identify one configuration of those motivations that leads to high intention to use mobile ad-blockers and two configurations leading to low intention. We contribute by identifying motivations driving the intention to use mobile ad-blockers and to motivation theory by examining the multidimensionality within configurations of intrinsic and extrinsic motivations and components of amotivation leading to a certain behavior. We empirically examine the role of amotivation, showing that amotivation can even override the influence of intrinsic and extrinsic motivations, which otherwise would lead to a certain behavior.

1 INTRODUCTION

There are two ways mobile device users can respond to ads. They can interact by actively looking at it, engaging with it cognitively, or even clicking on it to get more information (Ho and Bodoff 2014). Alternatively, they can avoid it by looking away, ignoring it, or skipping it (Seyedghorban et al. 2016). Given that a mobile device user doesn't want ads to be shown on her mobile device in the future, they typically install a mobile ad-blocker (PageFair 2016).

In 2019, a quarter of all mobile device users worldwide used mobile ad-blockers, and the number of new installations continues to rise (Perrin 2019). The lack of user interaction with ads puts the business model of many website operators at risk because they only get paid for promoting products if ads are shown to mobile device users (Aseri et al. 2020). Recent statistics indicate a loss of over 12 billion US dollars in potential sales through mobile ads blocked by mobile ad-blockers in 2020 in the US alone (Statista 2020). It remains a pressing issue for website operators to understand the underlying motivations behind increased mobile ad-blocker installation to probably include ads differently on their website and eventually be excluded from blocked pages and stabilize their website advertising income.

From a theoretical point of view, the motivations to use mobile ad-blockers are still underexplored (Gordon et al. 2021). Extant research focuses on advertising avoidance, presenting underlying reasons for avoiding ads on a desktop PC, such as irritation due to ads or goal impediment (Seyedghorban et al. 2016). Compared to a desktop PC, mobile devices are considered the most personalized technology we use in our everyday lives (Sutanto et al. 2013), so we suppose that the motivations to avoid ads on a mobile device are more diverse than those with a desktop PC. Beyond that, ad avoidance is a passive behavior shown by skipping the ad or looking away (Seyedghorban et al. 2016). Installing an ad-blocker requires action, so the motivations for those two behaviors differ. With that, we aim to use motivation theory (Deci and Ryan 1985; Vallerand 1997), suggesting that intrinsic motivation, extrinsic motivation, and amotivation influence human behavior to understand what motivates users to use mobile ad-blockers. So, our first research question (RQ) is:

RQ1: What intrinsic and extrinsic motivations and components of amotivation contribute to individual mobile ad-blocker use intention?

To answer RQ1, we undertook a qualitative study, interviewing current non-users of mobile ad-blockers in the pre-adoption phase (Limayem et al. 2007; Maier et al. 2015) to identify the motivations (or lack thereof) driving the adoption of mobile ad-blockers. Based on this study, we identified seven intrinsic motivations, extrinsic motivations, and components of amotivation that collectively drive individual intention to use mobile ad-blockers.

Motivation theory states that motivations are not equally important for different individuals (Vallerand 1997). This observation is mirrored in our qualitative study, where no motivational factors apply to all interviewees. For example, while for some individuals, an improved user experience was a strong motivator to use a mobile ad-blocker, others attributed the improved user experience with a subordinated role in influencing the intention to use mobile ad-blockers.

Beyond that, some interviewees reported expecting an improved user experience with a mobile ad-blocker but still had a low intention to use a mobile ad-blocker because they lacked the mobile competence to install one or felt certain reciprocity in being exposed to ads in return for free access to mobile websites and services. These findings suggest two things: First, present amotivation can override even strong intrinsic and extrinsic motivations, and second, whether individuals develop an intention to use mobile ad-blockers depends not on different separate motivations but on how they come together to influence behavior. We, therefore, aim to identify different configurations of motivational factors that lead to mobile ad-blocker use intention by integrating *multidimensionality* into motivation theory (Misangyi et al. 2016) and respecting variation in motivations yielding mobile ad-blocker usage. Therefore, we ask:

RQ2: What configurations of collective intrinsic and extrinsic motivations and components of amotivation lead to high respectively low individual mobile ad-blocker use intention?

To answer RQ2, we undertook a quantitative survey study (N=249) and used the configurational approach of qualitative comparative analysis (QCA). We derived one configuration leading to high intention to use mobile ad-blockers and two yielding low intention. To integrate both studies, we followed a mixed-methods approach (Reis et al. 2022; Venkatesh et al. 2013). This paper contributes to motivation theory by identifying multiple configurations of intrinsic and extrinsic motivation and amotivation leading to high and low intention to use mobile ad-blockers and by elaborating on the role of amotivation empirically. This study also contributes to ad avoidance research by revealing factors positively influencing motivation, which helps us better understand individuals' intention to use mobile ad-blockers.

2 THEORETICAL BACKGROUND

This section introduces motivation theory, forming the basis of this research and research related to mobile advertising and ad avoidance research.

2.1 Mobile Advertising and the Influence of User Behavior

There are three players within the mobile advertising process: the advertiser, issuing mobile ads, the publisher, displaying mobile ads, and the user, who is exposed to mobile ads (Schumann et al. 2014) and showing interaction, such as actively looking at it, engaging with it cognitively or clicking on it to receive more information (Cho 2003; Ho and Bodoff 2014). However, users unwilling to interact with mobile ads can show different behaviors, such as mobile ad avoidance. Depending on the user behavior, the relations and interactions between the players change (see Figure 1, relations and interactions modeled as arrows).

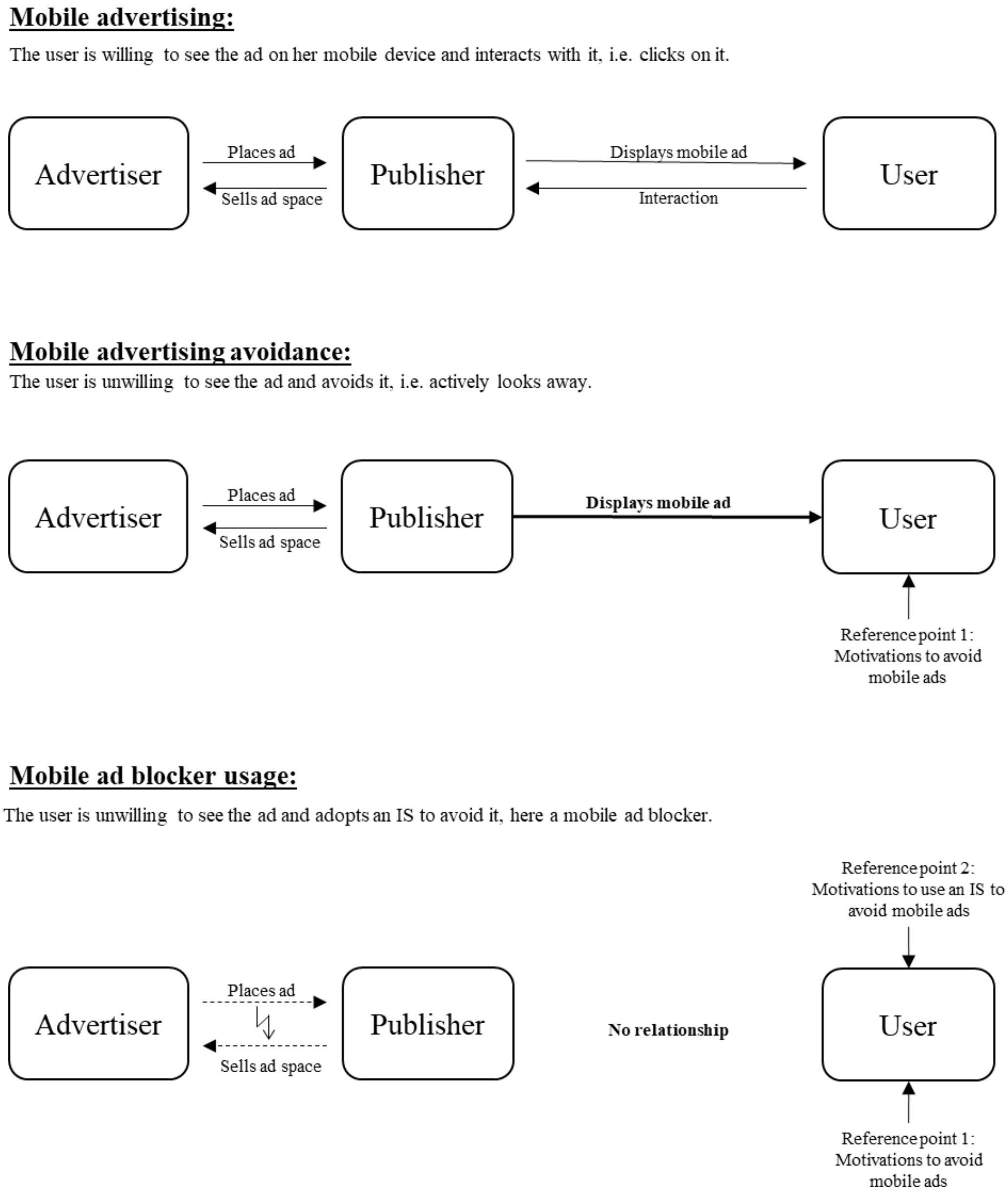

Figure 1. Mobile Advertising, Mobile Ad Avoidance, and Mobile Ad-Blocker Usage

2.1.1 Mobile Advertising Avoidance

Speck and Elliott (1997, p. 61) define ad avoidance as "*all actions taken by users that differentially reduce their exposure to ad content*." These actions can either express affective, cognitive, or behavioral avoidance (Cho and Cheon 2004), which, in the case of mobile ad avoidance, corresponds to looking away, being stressed by the ad, or ignoring or skipping the ad. The user's lack of interaction with the ad shifts the relationship between the publisher and the user from bilateral to **unilateral** (see Figure 1), disrupting the mobile advertising process in two ways. First, the advertiser wastes money because she is paying to display her mobile ads, but the user is avoiding the ad, so her ads will not have the desired effect (Kohli et al. 2015). Second, the publisher loses money, as the pure display of mobile ads, which is scrolled over or ignored, sells much cheaper than a user interaction, such as a longer retention time on the ad or clicking the ad (Asdemir et al. 2012).

The underlying motivations for users to avoid online ads, such as privacy concerns, irritation, goal impediment, dissatisfaction, intrusiveness, ad clutter, and financial constraints, have been studied in various contexts of online advertising, including email advertising (Baek and Morimoto 2012), display (Cho and Cheon 2004; Goldfarb and Tucker 2011; Sarial-Abi and Ulqinaku 2020; Seyedghorban et al. 2016), pop-up (Edwards et al. 2002), social media (Miltgen et al. 2019), pre-roll, and video ads (Campbell et al. 2017).

2.1.2 Mobile Ad-blocker Usage

In line with the definition of ad avoidance (Speck and Elliott 1997), we consider using a mobile ad-blocker as a technology-supported form of mobile advertising avoidance designed to reduce mobile ad exposure (Kannan et al. 2016). Although recent statistics register a continuous growth in mobile ad-blocker installations (Perrin 2019), previous research has largely ignored using a mobile ad-blocker as a technology-supported form of mobile advertising avoidance, going beyond the scope of extant research into behavioral mobile ad avoidance behavior (Kannan et al. 2016; Söllner and Dost 2019). Instead of skipping the mobile ad, the user actively adopts a technological tool to block such ads. This behavior changes mobile advertising far beyond mobile ad avoidance (see Figure 1) because mobile ad-blockers prevent the publisher from displaying the advertiser's ads to users via mobile devices. Consequently, due to the utilization of technology, the relationship between publisher and user is **annulled**, and the advertiser will not pay the publisher, threatening the publisher's advertising-based business model.

To examine motivations driving mobile ad-blocker use, we chose motivation theory (Ryan and Deci 2000; Vallerand 1997), which focuses on intrinsic and extrinsic motivational factors as well as amotivation, enabling us to consider how they collectively drive the intention to use mobile ad-blockers.

2.2 Motivation Theory

Motivation is concerned with how people’s needs and drivers move them to behave a certain way (Vallerand 1997), giving them an inner impetus to do something (Ryan and Deci 2000). Over time, motivation has come to be seen less as a unitary phenomenon and more as an orientation based on underlying internal and external attitudes and goals causing actions (Ryan and Deci 2000). Leveraging different existing theories treating motivation and human behavior, such as self-determination theory (Deci and Ryan 1985) or cognitive evaluation theory (Ryan 1982), Vallerand (1997) associates motivation with the constructs of *intrinsic motivation*, which relate to satisfaction or pleasure, *extrinsic motivation*, which moves individuals to do something for a separable outcome, and *amotivation* resulting from factors preventing individuals from being motivated (Pelletier et al. 1995; Ryan and Deci 2000). To fully understand underlying motivations, we must collectively consider all three types of motivation (Vallerand 1997, p. 278) regarding their influence on certain behaviors (Vallerand 1997). In line with prior research (Li et al. 2013), this study refers to these concepts as *motivation theory* (see Figure 2).

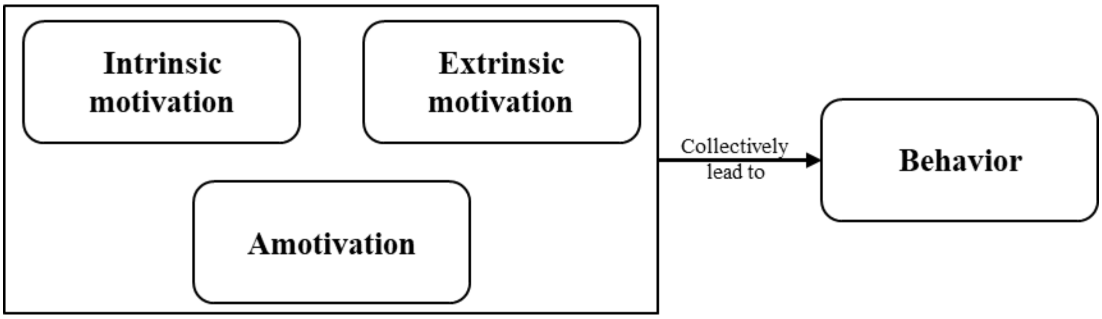

Figure 2. Motivation Theory (Adapted from Li et al. (2013))

2.2.1 Intrinsic Motivation

Intrinsic motivation is defined as an inner impetus driving individuals to act for satisfaction, fun, or challenge (Ryan and Deci 2000). Intrinsic motivation addresses personal needs, such as the inner pursuit of autonomy, competence, safety, health, satisfaction, enjoyment, or relatedness (Ryan and Deci 2000). Individuals differ in their intrinsic motivation to behave in a specific way. Not all individuals show an equal level of intrinsic motivation; some are not intrinsically motivated(Ryan and Deci 2000). That is where extrinsic motivation comes in.

2.2.2 Extrinsic Motivation

Extrinsic motivation is related to achieving external goals (Vallerand 1997). Individual behavior is directed by external regulations or benefits, such as social norms, punishments, pressure, monetary gains, or social advantages (Vallerand 1997). Extrinsic motivation is a primary driving force behind human behavior (Ryan and Deci 2000).

2.2.3 Amotivation

Amotivation refers to everything that impedes individuals from performing a motivated behavior and can be defined as the lack of the intention to act because of certain factors (Ryan and Deci 2000). Amotivation results from not valuing an activity, not feeling competent to perform it, being opposed to it, or not believing it will yield a desired outcome (Ryan and Deci 2000). Amotivation can impede every task or desired behavior, despite the presence of intrinsic and extrinsic motivations, and needs to be considered to fully explain the motivators to perform a certain behavior(Ryan and Deci 2000). Therefore, extant research on motivation theory argues that we can only explain certain behavior by collectively considering intrinsic motivation, extrinsic motivation, and components of amotivation(Vallerand 1997). The following example illustrates this interplay.

> If Alice loves to go out for dinner because she enjoys how the food is prepared and presented (intrinsic) and saves a lot of time and effort, which she values more than the cost of eating out (extrinsic), we might conclude that Alice always eats out. Now, imagine Alice is in China but does not speak Chinese. She may still enjoy how the food is prepared and still want to save time and work. However, because she does not speak the language or have someone to help her, her perceived lack of competence prevents her from eating out, and she may stay at home despite intrinsic and extrinsic motivations to eat out.

This paper strives to identify the underlying motivations that collectively drive individual intention to use mobile ad-blockers and their variations. Those motivations arise from two reference points: The intention to avoid mobile ads and the intention to adopt technology to avoid them. So, we turn to motivation theory in mobile advertising and information systems research as a starting point.

2.3 Motivation Theory in Advertising and Information Systems Research

Motivation theory has been widely used in extant advertising and information systems research to explain behavior in various contexts, such as technology usage behavior (Li et al. 2013; Wu and Lu 2013), consumer purchase behavior (Hohenberg and Homburg 2016) or knowledge management in organizations (Ko et al. 2005) (see Appendix A for a detailed review). However, most research into motivation in the advertising and information systems context only considers intrinsic motivation and extrinsic motivation, leaving out amotivation's role in driving individual behavior or conceptualizing amotivation solely as the absence of motivation instead of certain components resulting in the lack or override of motivation (James et al. 2019). In addition, extant literature has considered behavior arising from one reference point only. For example, studies explaining the motivation behind adopting a new technology refer to motivations contributing to using new technology but not abandoning the old (Li et al. 2013). Articles examining the purchase of a product refer to motivations driving individuals to buy that specific product only but do not consider any other (Kim et al. 2018). Let's think of individuals' intention to use mobile ad-blockers. The motivation arises from two reference points: motivations driving the intention to avoid mobile ads and the intention to adopt a certain technology to avoid them.

Current research has not identified the underlying motivations that collectively drive the intention to use mobile ad-blockers. As such, this paper fills several gaps in mobile advertising and advertising avoidance research and expands motivation theory using a mixed-methods approach.

3 MIXED-METHODS APPROACH

We use a mixed-methods approach to answer our two research questions(Reis et al. 2022; Venkatesh et al. 2013). Selecting a suitable sample of current non-users of mobile ad-blockers, we conducted one qualitative and one configurational study based on a configurational approach.

3.1 Study 1: Motivations Contributing to Individuals' Use of Mobile Ad-blockers

Study 1 identifies the intrinsic and extrinsic motivations and components of amotivation that contribute to individual intention to use mobile ad-blockers.

3.1.1 Data Collection

We conducted 44 semi-structured interviews (see Table 1 for demographics), a sufficiently large sample for interviews in a mixed-methods approach (Collins et al. 2006). Following prior literature indicating that the underlying motivations of adopters and users differ (Maier et al. 2015), we sought to interview participants who were aware of but had never used a mobile ad-blocker before. All interviews followed a semi-structured guideline (see Appendix B) and were conducted during an extracurricular economic academy program for students. We found nonstudent participants using the snowball strategy. Interviews lasted approximately 20 minutes and were recorded and transcribed fully with the consent of our interviewees.

Age (in percent) Mean 33.0; SD 12.5		Biological sex (in percent)		Daily time online* (in percent) Mean 2.1; SD 1.5		Highest education level (in percent)	
≤ 20	25.0	Male	69.0	≤1h	40.9	High school	57.0
21-30	27.3	Female	31.0	1-2h	9.1	Bachelor	26.0
31-40	25.0			2-3h	38.6	Master	17.0
> 40	22.7			3-4h	4.5		
				>4h	6.9		
Note: SD = standard deviation; * refers to using the Internet on a mobile device via the browser or apps.							

Table 1. Demographics Study 1

3.1.2 Data Analysis

To analyze the interviews, we transcribed them and did multiple rounds of coding using MAXQDAplus following the coding scheme by Myers (2019). We show an overview of this approach in Table 2 (see Appendix C for a coding example).

Step	Summary of the applied procedure
First step: *descriptive coding*	Identification of passages of the transcribed interview and assignment of 26 descriptive codes.
Second step: *interpretive coding*	Applying interpretive coding on the 26 descriptive codes from the first step reveals seven interpretative codes.
Third step: *review of interpretive coding*	Ensuring objective coding through a review of the interpretive codes and calculating the inter-judge reliability of 0.93 (Boyatzis, 1998).
Fourth step: *categorizing interpretive codes*	Categorizing the interpretive codes to ‘extrinsic motivation,’ ‘intrinsic motivation,’ and ‘amotivation’.

Table 2. Overview of the Four-Step Coding Approach (Adapted from Myers (2019))

3.1.3 Results: Qualitative Inferences

In summary, we identified seven motivations that, as a collective, contribute to individuals’ intention to use mobile ad-blockers and classified them based on motivation theory (see Figure 3). We identified *reduced well-being through mobile ads* and *improved privacy protection* as intrinsic motivations*, improved user experience, increased performance, improved security* as extrinsic motivations, and *perceived mobile incompetence* and *perceived reciprocity* as components of amotivation.

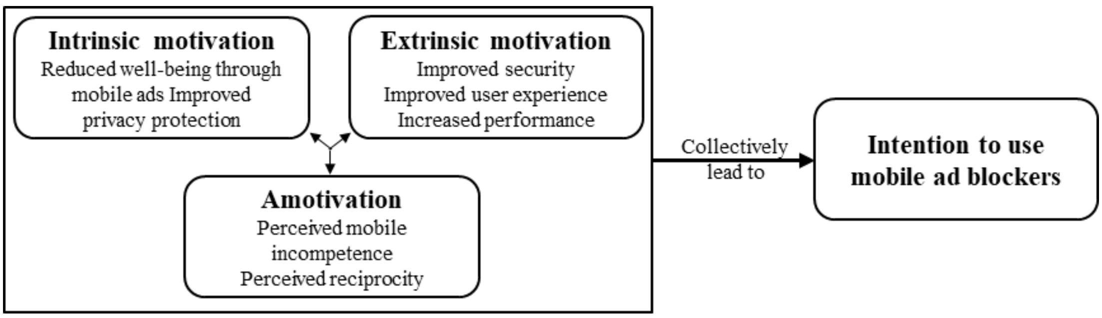

Figure 3. Motivational Factors Clustered Using Motivation Theory

Reduced well-being through mobile ads: The interviewees reported being increasingly stressed, exhausted, or feeling fatigued when browsing websites with ads on their mobile devices. These negative reactions to mobile ads reduce their overall well-being while browsing the Internet. Prior research identifies individual well-being as a state of affective and cognitive satisfaction resulting from the individual's inner impetus to achieve a certain fulfillment, happiness, and quality of life with their actions (Diener et al. 2018), browsing the Internet. In line with research treating display advertising (Cho and Cheon 2004), being exposed to mobile ads has been reported by the interviewees as annoying, distracting, and impeding the goal pursued while browsing mobile websites and, therefore, is opposed to the inner impetus to achieve fulfillment and happiness. We classify reduced well-being through mobile ads as intrinsic motivation.

Improved privacy protection: Improved privacy protection is classified as intrinsic motivation (Vallerand 1997) because of individuals' inner need for safety. In line with advertising research (Baek and Morimoto 2012; Tucker 2014), improved privacy protection means relieving individuals' concerns about being tracked without permission.

Improved security: Several interviewees stated they feared malicious ads, such as harmful JavaScript code, and thus intended to use a mobile ad-blocker to protect their mobile devices. Therefore, we classify improved security as an extrinsic motivation (Vallerand 1997). In line with information security research (Johnston and Warkentin 2010), we understand improved security as the decreased risk of getting infected with spyware, which drives the intention to use mobile ad-blockers.

Improved user experience*:* Improved user experience, classified as extrinsic motivation, aiming at better usability and less irritation (Zhang 2011), enhances the intention to use mobile ad-blockers. In line with research on user experience in online environments (Hassenzahl and Tractinsky 2006; Zhang et al. 2011), we define improved user experience as a better usability or design experience with less irritation.

Increased performance: Interviewees stated that they intend to use a mobile ad-blocker to shorten webpage loading time, which saves time and Internet capacity if no ads are loaded. Increased performance reflects an extrinsic motivation, addressing the external goal of greater efficiency (Gefen and Straub 2000). In line with research on website quality (Wells et al. 2011), we define increased performance as a shorter loading time of mobile sites.

Perceived reciprocity*:* Some interviewees stated that they understand and accept the need for mobile websites to display ads to provide free content to their users. The perceived reciprocity, defined as the feeling of getting something in return for exposure to ads (Schumann et al. 2014), leads to a lower intention to use mobile ad-blockers. We classify perceived reciprocity as a component of amotivation.

Perceived mobile incompetence*:* The interviewees also mentioned that they do not intend to use a mobile ad-blocker because they feel unable to install and use a mobile ad-blocker. Perceived mobile incompetence contributes to amotivation, reflecting individuals' judgment of their inability to install and operate mobile ad-blockers, leading to a lower intention to use mobile ad-blockers (adapted from Compeau and Higgins (1995)).

Intention to use mobile ad-blockers*:* Concerning the intention to use mobile ad-blockers, not all interviewees reported the same level of intention. While some interviewees showed a high intention and reported that they would definitely get a mobile ad-blocker soon to leverage the associated benefits and increase their well-being, others were unsure whether to install one. The interviewees also varied in their perceptions of specific motivations influencing the intention to use. For example, while for some interviewees, an improved user experience was a strong motivator to use a mobile ad-blocker, others rated an improved user experience as unimportant in influencing the intention to use mobile ad-blockers. Interestingly, some interviewees even reported expecting an improved user experience with a mobile ad-blocker but still had a low intention to use a mobile ad-blocker. Most interestingly, those interviewees who reported being unsure whether they would install a mobile ad-blocker and showed a relatively low intention were not necessarily those who had difficulties in installing one but those who perceive a certain reciprocity, so the obligation to receive mobile ads in return for free access and content, even though they were aware of the benefits. Study 2 digs deeper into this.

3.2 Study 2: Configurations Leading to Individuals' Intention to Use Mobile Ad-blockers

Study 2 addresses our second research question, which identifies configurations of collective intrinsic and extrinsic motivations and components of amotivation that lead to either a high or low intention to use mobile ad-blockers.

3.2.1 Data Collection

We prepared an online survey (for demographics, see Table 3) using the same sampling strategy as in Study 1 and administered the survey on a crowdwork platform. We did not collect any traceable or personal data outside the demographics.

Age (in percent) Mean = 33.0; SD = 9.8		**Gender** (in percent)		**Daily time online*** (in percent) Mean = 3.9; SD = 2.5		**Highest education level** (in percent)	
≤ 20	7.26	Male	62.7	<1h	10.1	High school	29.9
21-30	43.15	Female	37.3	1-2h	19.7	Bachelor	40.7
31-40	33.87			2-3h	17.2	Master	30.4
>40	45.7			3-4h	23.5		
				>4h	29.4		
Note: SD = standard deviation; * refers to using the Internet on a mobile device via the browser or apps.							

Table 3. Demographics Study 2 (n = 249)

In line with recommendations (Lowry et al. 2016), we took several measures to ensure high-quality answers. We implemented robot questions to filter out bots or participants not paying attention. Also, we used five screening questions to ensure that we only have participants who are aware of mobile ad-blockers, have a mobile device, and have no ad-blocker in use. Additionally, we implemented three attention tests to filter out participants who only click randomly. Overall, 2,189 crowd workers clicked on our invitation link to participate in the survey, and 249 successfully passed all our implemented measures. The sample is appropriate (conditions/sample size ≥ 0.2) for the underlying number of seven conditions, which is below the maximum recommended number of eight (Marx 2006).

3.2.2 Measures and Measurement Model

To capture the motivations identified in Study 1 and the intention to use a mobile ad-blocker, we adapted measurement items used in previous research to the context of mobile ad-blockers to ensure *content validity.* An overview of the items is included in the Appendix (see Appendix D). We used a 7-point Likert agreement scale ranging from 1 = ‘strongly disagree’ to 7 = ‘strongly agree.’

To assess the validity and reliability of the construct measures, we calculate Cronbach’s alpha, which ranges from 0.87 to 0.98, exceeding the threshold of 0.70 (Nunnally 1978). We conducted a rotated factor analysis and test validated *indicator validity.* All but one item for perceived mobile incompetence had a loading greater than 0.70. We removed the item and repeated the analysis to attest to indicator validity, as all loadings exceeded 0.707. To test for *construct reliability*, we also compute composite reliability (CR) scores, ranging between 0.88 and 0.99, exceeding the required minimum value of 0.70 (Bagozzi and Yi 1988). The computed average variances extracted (AVE) exceeded the standard threshold 0.50 and ranged from 0.71 to 0.94. Furthermore, the square root of the AVE is greater than the corresponding correlations of the constructs, which attests to *discriminant validity.* We also calculated the heterotrait-monotrait (HTMT) ratio, which was 0.72 and thus below the absolute $HTMT_{0.85}$ criterion (Henseler et al. 2014). To test for a common method bias (Podsakoff and Organ 1986), we ran

Harman's single-factor test, which reveals that one factor only explains 42.31 percent of the variance for the measures, which is below the recommended threshold of 50 percent. Furthermore, we examined the correlation matrix in applying the procedure specified by Pavlou et al. (2007), which reveals that no high correlations are present (see Table 4).

		Mean	SD	AVE	CR	α	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
(1)	*Improved user experience*	5.34	1.35	0.71	0.88	0.87	0.84							
(2)	*Increased performance*	5.26	1.48	0.80	0.92	0.91	0.60	0.89						
(3)	*Improved security*	4.84	1.71	0.86	0.95	0.94	0.40	0.38	0.93					
(4)	*Improved privacy*	4.62	1.63	0.93	0.98	0.97	0.44	0.41	0.73	0.96				
(5)	*Reduced well-being*	5.11	1.42	0.72	0.93	0.94	0.42	0.39	0.61	0.59	0.85			
(6)	*Mobile incompetence*	3.02	1.55	0.93	0.92	0.93	-0.04	-0.09	0.09	0.11	0.02	0.96		
(7)	*Reciprocity*	4.81	1.28	0.78	0.94	0.95	-0.08	0.01	-0.07	-0.08	-0.19	-0.04	0.88	
(8)	*Intention to use*	4.38	2.04	0.94	0.98	0.98	0.43	0.25	0.44	0.39	0.49	-0.06	-0.26	0.97
Note: The square root of AVE is listed on the diagonal of bivariate correlations; SD = standard deviation; AVE = average variance extracted; CR = composite reliability; α = Cronbach's alpha														

Table 4. Descriptive Statistics and Discriminant Validity

3.2.3 Data Analysis

To analyze the data, we proceeded with a four-step approach (Mattke et al. 2022).

Step 1. Calibration. In the first part, we need to convert the interval-scaled variables of a research model into fuzzy sets. We use direct calibration by using three different anchors (anchor for full-non-membership in the set, crossover point, and full membership in the set). For variables measured on a 7-point Likert scale, using the values 1, 4, and 7 as anchors is common. Other variables, such as gender, can be transformed into crisp sets only having two values.

Step 2. Analysis for necessary conditions. We test whether the presence of a single condition or the absence of a single condition is necessary for the outcome. We use the calibrated data and test whether the presence of a condition or the absence of a condition is necessary. A necessary condition must exceed the consistency threshold of 0.90, the coverage threshold of 0.60, and the relevance of necessity threshold of 0.60.

Step 3. Analysis for sufficient configurations of conditions leading to a high outcome. We first need to construct the truth table based on the calibrated data to examine which sufficient configurations lead to a high outcome. This means that we list all existing configurations in a truth table. To examine which of them is sufficient for a high outcome, we second determine a consistency threshold (needs to exceed 0.85), a proportional reduction in inconsistency (PRI) threshold (needs to exceed 0.75), and a frequency threshold (higher than three). The frequency threshold reduces the truth table to configurations found at least three times. The consistency threshold then determines whether a configuration (with at least three observations) is sufficient for the outcome. The PRI thresholds reduce the truth table to configurations that are only sufficient for the presence of the outcome but not for the absence. In summary, this step results in a reduced truth table containing configurations with at least three observations determined as sufficient or insufficient for the outcome. We third apply the Quine-McCluskey algorithm to simplify the configurations, which produces the solution (in terms of the intermediate solution). Additionally, the algorithms produce a complex solution and a parsimonious solution. Based on them, we, fourth, can specify core conditions that appear in the parsimonious and the intermediate solution.

Step 4. Analysis for sufficient configurations leading to a low outcome. The same procedure of Step 3 is repeated, but instead of examining configurations for a high outcome, we can examine which configurations lead to a low outcome in this step.

3.2.4 Results: Configurational Inferences

Applying the data analysis described above, we revealed no necessary conditions. The analysis of sufficient configurations revealed one configuration leading to a high intention to use and two configurations leading to a low intention to use (see Figure 4).

	High intention C1	Low intention C2	Low intention C3
Reduced well-being through mobile ads	●	⊗	⊗
Improved privacy protection	●	⊗	⊗
Improved security	●	⊗	⊗
Improved user experience	●	⊗	●
Increased performance	●	⊗	●
Perceived reciprocity	⊗	●	●
Perceived mobile incompetence	⊗		⊗
Raw coverage	0.29	0.19	0.23
Unique coverage	0.29	0.08	0.11
Consistency	0.91	0.95	0.87
Solution coverage	0.29	0.30	
Solution consistency	0.91	0.89	

Note: Black circles (●) indicate the presence of a condition and crossed-out white circles (⊗) indicate the absence of a condition. Blank spaces ( ) indicate a 'don't care situation,' in which the condition may be either present or absent and, therefore, plays a subordinate role in the configuration.

Figure 4. Graphical Representation of the Results

The solution coverage is 0.29 for the configuration leading to high intention to use and 0.30 for low intention to use. The solution consistency and the consistency of each configuration are above 0.75, as recommended in QCA literature (Schneider and Wagemann 2012). The raw coverage of the configurations ranges from 0.19 to 0.23, which shows an adequate proportion of membership in the outcome. The unique coverage values range from 0.08 to 0.11 and, therefore, exceed the value of 0, indicating that each configuration contributes to explaining the outcome. Our calibration is robust to sensitivity analysis to the sample varying the anchors of the calibration (Ordanini et al. 2014; Park et al. 2017).

Regarding content, we identified configuration C1, which shows that an individual needs to be extrinsically and intrinsically motivated and perceive no amotivation to show a high intention to use a mobile ad-blocker. In contrast, configurations C2 and C3 show that when individuals are neither extrinsically motivated nor intrinsically motivated but show amotivation, or amotivation outperforms the influence of extrinsic motivation, they show a low intention to use ad-blockers.

3.3 Combined Results: Meta-Inferences

Within this subsection, we deduce the results gathered from integrating both studies in one approach, in short: the existing meta-inferences (Reis et al. 2022). We achieved predominantly convergence within our qualitative and configurational inferences. This attests to good inferences and strengthens the results (Venkatesh et al. 2013).

Both results confirm that individuals with a high intention to use mobile ads must be intrinsically motivated to avoid them and use a mobile ad-blocker actively. In this context, they assess mobile ads as annoying and invasive, reducing their well-being and aiming at improved privacy protection when blocking ads.

Further, our qualitative inferences suggest that extrinsic motivations also contribute to a high intention to use mobile ad-blockers. However, our configurational study shows that some of them can have an asymmetric influence on intention to use, as this motivation can be part of configurations leading to a high (C1) and a low intention to use mobile ad-blockers (C3). So, on the one hand, individuals recognize the installation of a mobile ad-blocker as a possibility to increase their security and improve their performance and user experience while browsing online. Most research on ad avoidance identifies irritation as motivation to avoid ads. Further, receiving ads on mobile devices can be especially irritating due to limited screen size and battery loading (Fang et al. 2006). Also, the mobile phone depicts a personal device with personal data and limited internet capacity (Sutanto et al. 2013). Therefore, improving user experience, performance, and security might be especially important in the mobile context. On the other hand, two of these extrinsic motivations can also contribute to a low intention to use mobile ad-blockers when combined with components of amotivation, as in C3. Whether an improved user experience and improved performance contribute to a high or low intention to use mobile ad-blockers depends on the combination of other motivations and components of amotivation.

Last, both results show that present amotivation contributes to a low intention to use mobile ad-blockers and even overrides present intrinsic or extrinsic motivations. This finding is in line with recent statistics (Statista 2018) showing that not all individuals aware of ad-blockers and their advantages also use them. Therefore, something must inhibit individuals from developing a high intention to use mobile ad-blockers. We suggest that this is the effect of perceived mobile incompetence and perceived reciprocity.

4 DISCUSSION

The number of active mobile ad-blocker users is rising steadily, causing economic damage to publishers relying on fees paid by advertisers for displaying mobile ads to users on their mobile devices (PageFair 2016). The applied mixed-methods design helped us to identify and understand the motivations and their role in determining a high or low intention to use mobile ad-blockers. Based on motivation theory and the triangulation of our study results, we can deduce the following:

First, individuals with high intention to use mobile ad-blockers must be intrinsically and extrinsically motivated, while amotivation is absent. Second, individuals with a low intention to use a mobile ad-blocker perceive amotivation that can even override the influence of present motivations, as theorized in motivation theory (Vallerand 1997). Third, the role of motivations in determining a certain behavior, here using a mobile ad-blocker, can only be assessed by examining intrinsic motivation, extrinsic motivation, and amotivation in combination.

4.1 Theoretical Contributions and Future Research

To clearly distinguish between a result and a theoretical contribution, we present extant research, results of this research, contributions, and future research for each research question.

RQ1: What intrinsic and extrinsic motivations and components of amotivation contribute to individual mobile ad-blocker use intention?

Extant research has not identified the motivations driving individual intention to use mobile ad-blockers. Even though related research on ad avoidance and IS adoption reveals some factors that may be related to the topic at hand, neither IS nor adoption research is powerful enough to explain the intention to use mobile ad-blockers fully, as we need to integrate both reference points, the avoidance of mobile ads and the adoption of the mobile ad-blocker.

This research integrates both reference points and first uses motivation theory to identify intrinsic and extrinsic motivations and amotivation driving individual intention to use mobile ad-blockers. The motivations arise from both reference points, meaning that we identify motivations related to avoiding ads and from the context of IS adoption. Namely, we identified *reduced well-being through mobile ads*, *improved privacy protection*, *improved security*, *improved user experience*, *increased performance, perceived reciprocity,* and *perceived mobile incompetence* as motivations shaping individual intention to use mobile ad-blockers.

Contribution-wise, most of the identified motivations are consistent with existent research on advertising avoidance or technology adoption (Baek and Morimoto 2012; Campbell et al. 2017; Cho and Cheon 2004; Edwards et al. 2002; Venkatesh and Davis 2000). We validate and specify those motivations for the context of mobile ad-blocker usage and integrate both disciplines to understand the three types of motivation arising from two reference points: the avoidance of mobile ads and the adoption of the ad-blocker as technology and, as a collective, driving the intention to use mobile ad-blockers. Current research on motivation theory in the marketing or information systems context has widely ignored amotivation as a driving factor (see Appendix A).

Apart from adoption, **future research** could identify the relevant motivations for continuous usage and discontinuation, as our pre-test already showed that there might be differences within the phases of the IT usage lifecycle (Maier et al. 2015). Further, there might also be differences concerning the perspective of the study: Whereas we focused on the individual, future research could elaborate on the phenomenon from an organizational perspective or even from the perspective of ad-blocker providers, as the phenomenon of ad-blockers is still under-researched (Gordon et al. 2021).

RQ2: What configurations of collective intrinsic and extrinsic motivations and components of amotivation lead to individual mobile ad-blocker use intention?

Extant research applying motivation theory has focused on a linear examination of behavior arising from one reference point. Motivation theory, however, states that the interplay between all three types of motivation (intrinsic, extrinsic, and amotivation) collectively drives behavior.

This research examines the logical connectivity between the identified factors and the underlying psychological dynamics expressed through configurations of motivations leading to individual intention to use a mobile ad-blocker. These configurations can be seen as instantiations of the derived research model. Thereby, we examine the variance in the perception of single motivations and the role of amotivation: First, individuals having a high intention to use mobile ad-blockers need to be intrinsically and extrinsically motivated, while amotivation is absent. Second, individuals with low intention to use a mobile ad-blocker perceive amotivation that can even override the influence of present motivations, as theorized in motivation theory (Vallerand 1997). Third, the role of motivations in determining a certain behavior, here using a mobile ad-blocker, can only be assessed by examining intrinsic motivation, extrinsic motivation, and amotivation in combination.

Regarding **contributions**, Studies applying motivation theory to marketing and information systems research have focused solely on intrinsic and extrinsic factors and have largely ignored the effects of amotivation. We contribute to motivation theory (Vallerand 1997) by empirically examining the role of amotivation, showing besides the theorized separate negative effect of amotivation, also in combination, amotivation can actually override existing motivation and impede behavior. Further, we identified configurations of intrinsic and extrinsic motivations and amotivation, which lead to high, respectively low, individual intention to use mobile ad-blockers. We contribute to the theory by showing that motivation is not linear but multidimensional, and those different motivational elements vary in their importance in causing a certain behavior. We contribute that motivations driving the examined behavior can arise from multiple reference points, in contrast to research only considering one. Future research applying motivation theory should respect this contribution and explain behavior from a multidimensional perspective. Our interviews reveal that mobile ads can have a demanding impact on individuals, leading to stress. Related research in the stress context (Lazarus and Folkman 1984) shows that individuals try to escape from demanding situations by coping with the stressors differently. The literature describes approach and avoidance coping (Carver 2006; Roth and Cohen 1986). The underlying basic assumption of these two concepts is that avoidance coping tries to reduce stress by distancing oneself from the anti-goal state, here the confrontation with mobile ads, and that approach coping tries to take control and action away from the anti-goal state towards the goal state, here an ad-free environment. Approach coping thereby is associated with a high degree of self-regulation (Carver 2006), control autonomy and explains why the inner impetus to achieve autonomy and control, so the intrinsic motivation, drives individuals to take action, so install a mobile ad-blocker to achieve the goal state of an ad-free environment. These two concepts also stress the difference between ad avoidance, focusing on the anti-goal state of being confronted with mobile ads, and mobile ad-blocker usage, esteeming from two reference points to get away from the anti-goal state towards the goal state, here an ad-free environment.

We encourage **future research** to intensify the examination of amotivation in terms of separate but foremost combined effects with other motivations. Our results indicate that perceived mobile incompetence might not have been the driving amotivation behind a low intention to use mobile ad-blockers. Future research could think about a better categorization of components of amotivation, such as strong or subordinated, just impeding behavior, or even overriding present motivations.

4.2 Practical Implications

From a practical perspective, we help website operators, i.e., publishers, who get paid by advertisers investing in mobile advertising to display their ads, better understand why individuals intend to use mobile ad-blockers. Consequently, publishers can address those issues and eventually prevent mobile device users from installing a mobile ad-blocker, thereby cutting off their relationship with the publisher, which causes economic damage to publishers and advertisers and threatens publishers’ business models on the Internet. We discussed the practical implications of this paper with practitioners from a large online advertising agency taking the role of the publisher. The main takeaways of these discussions were the following.

(1) Stress the reciprocity of getting free access to websites and services for exposure to mobile ads. Our qualitative and configurational inferences show that perceived reciprocity is a component of amotivation, impeding the intention to use mobile ad-blockers and even overriding existing extrinsic motivations. This means that even individuals aware of mobile ad-blockers and valuing their benefits develop a low intention to install one if they perceive getting something in return for being exposed to mobile ads, at least for specific websites.

(2) Create a stress-free mobile advertising environment. The interviews and the configurational study show that exposure to mobile ads can reduce individuals' well-being, leading to stress-coping reactions in terms of ad avoidance or mobile ad-blocker use. Reducing the amount and invasiveness of mobile ads and the goal impediment through mobile ads can reduce the demanding effects of mobile advertising and reduce the necessity to cope with them.

(3) Be transparent and inform better. Considering the privacy and security concerns, publishers need to raise transparency concerning the data collection and tracking involved in mobile advertising. As revealed, leaving individuals in the dark about who is collecting what data about them fosters the use of mobile ad-blockers. Practitioners also revealed that ad-blockers eventually collect a similar amount of data and, therefore, might depict a security and privacy risk themselves, which website users should be informed about.

4.3 Limitations

The study is not free of limitations. To explain individual intention to use mobile ad-blockers, we use motivation theory and base our findings on indirect experiences and beliefs of current non-users. Even though direct experiences and beliefs could predict behavior better, concluding factors from indirect experiences is still valid and the only possibility to study the pre-adoption phase (Karahanna et al. 1999). The number of interviewees is limited to 44 within one specific population at one specific point in time, which reduces the generalizability of this study. Yet, according to research, this should not be regarded as a criterion of reduced quality of the qualitative study (Sarker et al. 2013). The online survey resulted in a total of 249 data sheets, which we used to analyze necessary and sufficient conditions for individuals to intend to use mobile ad-blockers. This also depicts a restriction in generalizability.

5 CONCLUSION

In response to the rising trend of mobile ad-blocker use causing high revenue losses for online publishers, we follow a mixed-methods approach, including interviews, surveys, and fsQCA, to understand what leads to individual intention to use mobile ad-blockers. We draw on motivation theory and identify intrinsic and extrinsic motivations and components of amotivation. This reveals one configuration of motivations leading to a high individual intention to use mobile ad-blockers and two configurations leading to a low intention to use mobile ad-blockers. Furthermore, we specify the unequal effects of motivations on intention to use mobile ad-blockers and examine the role of amotivation empirically. Our research contributes to motivation theory, expands the understanding of the use of mobile ad-blockers theoretically, and provides valuable implications to online publishers in facing the challenge of rising mobile ad-blocker use.

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APPENDIX A: LITERATURE REVIEW MOTIVATION THEORY

Table 5 lists existing research applying motivation theory in advertising and information systems research. The review is based on top marketing and information systems journals, encompassing the basket of eight relevant marketing journals (JMR, JoM, JCR, MS, JAP, JoR, JoCP, JoIA, JoAR, IJoA, PM) and the journal of advertising as guiding domain journal.

Paper	Context	Intrinsic	Extrinsic	Amotivatio	Reference point	Major findings
Alam and Campbell (2017)	Volunteers in cultural crowdsourcing	X	X		1	Volunteers initially show intrinsic motivations, though both intrinsic and extrinsic motivations play a critical role in their continued participation.
Brown and Lahey (2015)	Paying off debt in small payments	X			1	Paying off debt in small payments creates intrinsic motivation, which encourages individuals to become debt-free.
Burroughs et al. (2011)	Driving creativity in product development	X	X		1	Not only monetary rewards but also inner challenge and joy lead to higher creativity.
Choi and Fishbach (2011)	Choosing a product	X	X		1	Free choice vs. directed choice shows that an intrinsically motivated choice increases the need to obtain a product.
Haas and Kenning (2014)	Consultation of Salespeople	X	X		1	Only the combination of intrinsic and extrinsic motivators drives individuals to consult salespeople.
Hines (1973)	Job satisfaction	X	X		1	Interpersonal relationships are as important as salaries.
Hohenberg and Homburg (2016)	Cultural differences in innovation selling	X	X		1	Motivators depend on culture. We need to consider local intrinsic and extrinsic motivators to sell innovation.
Hsieh et al. (2011)	Digital inequality	X	X		1	Intrinsic and extrinsic motivation as a driver of socioeconomically disadvantaged intention to use ICTs.
Hulin (1969)	Community effects on job satisfaction	X	X		1	Integration of social factors among external factors for determining job satisfaction.
Jain et al. (2009)	Advertising approach vs avoidance	X	X		1	One needs to address outcome-oriented individuals as well as process-oriented individuals.
James et al. (2019)	Fitness trackers	X	X	X	1	Intrinsic regulation and extrinsic regulation, amotivation here considered as the lack of regulation.
Jung et al. (2020)	Online word-of-mouth referral programs	X	X		1	Intrinsically motivated promotion is perceived as more authentic than extrinsically, financially motivated promotion.
Ke et al. (2012)	Adoption of enterprise system	X	X		1	Increasing intrinsic motivators helps workers to explore the new system.
Kim and Ahn (2017)	Rewards in customer loyalty programs	X			1	Intrinsic motivation to participate in customer loyalty programs is higher, with fewer constraints concerning reward.
Kim et al. (2018)	Customer choice of uniqueness vs. conformity	X	X		1	Free choice increases autonomy and, therefore, purchase intention.

Ko et al. (2005)	Knowledge transfer in ERP implementation	X			1	Intrinsic motivators increase proper knowledge transfer.
Kraimer et al. (2011)	Organizational career opportunities	X	X		1	Identification of motivators for career development.
Laran and Janiszewski (2011)	Regulation behavior	X	X		1	A task can be perceived as fun or work, which influences regulation behavior.
Lowry et al. (2013)	Hedonic motivation systems	X	X		1	Hedonic motivation systems lead to adoption more readily than utilitarian systems.
Oyserman and Schwarz (2017)	Consumer behavior	X	X		1	Conservatism has an influence on the consumer.
Rahrovani and Pinsonneault (2020)	Motivational antecedents of innovative IT use and innovation with IT	X	X		1	Intrinsic motivation is an antecedent of innovative IT use, and extrinsic motivation is an antecedent of both behaviors.
Rockmann and Ballinger (2017)	Intrinsic motivation among on-demand workers	X	X		1	On-demand workers are intrinsically motivated and develop organizational identification.
Sen et al. (2008)	Open source software development	X	X		1	Developers are driven by intrinsic and extrinsic motivators when choosing an OSS to join.
Suher and Hoyer (2020)	Impulsive buying	X	X		1	Intrinsic and extrinsic motivations change during a shopping trip
Turel et al. (2011)	Technology addiction	X	X		1	Motivation and cognitive factors contributing to online auction addiction.
Von Krogh et al. (2012)	Open-source software	X	X		1	Intrinsic and extrinsic motivators to develop high-quality software.
Wu and Lu (2013)	System use behavior in the utilitarian, hedonic, dual-purposed context.	X	X		1	Different motivators are not equally important for different kinds of systems.
This paper	**Mobile ad-blocker**	**X**	**X**	**X**	**2**	**Understand how intrinsic and extrinsic motivation and amotivation collectively drive individual intention to use a mobile ad-blocker.**

Table 5. Literature Review on Motivation Theory in IS and Advertising Research

APPENDIX B: SEMI-STRUCTURED INTERVIEW GUIDELINE

We used the semi-structured interview guideline presented in Table 6 for the 44 interviews with current non-users of mobile ad-blockers in Study 1.

0 Demographic and screening questions
0.1 Can you give us some insights into your studies/professional experience? 0.2 How would you describe your mobile self-efficacy? 0.3 Have you ever heard of ad-blockers or mobile ad-blockers? 0.4 Have you ever used an ad-blocker on your mobile device?
1 General question on ad-blocker usage
1.1 What would change in your browsing experience if you use an ad-blocker? 1.2 Do you see some advantages or disadvantages? 1.3 Would you consider using an ad-blocker on your mobile device? Why?
2 Motivations contributing to the intention to use mobile ad-blockers
2.1 Are specific motivations contributing to the decision to use a mobile ad-blocker? 2.2 Which of them are of high importance?
3 Motivations inhibiting the intention to use mobile ad-blockers
3.1 Are specific motivations hindering the decision to use a mobile ad-blocker? 3.2 Which of them are of high importance? 3.3 Can they outweigh the positive, contributing motivations?

Table 6. Interview Guideline

APPENDIX C: CODING APPROACH

Our coding approach is based on the interpretive/descriptive coding approach presented by Myers (2019). Table 7 shows the results of the four-step approach. Each row displays one motivation factor. The first column shows an exemplary quotation illustrating the motivation factor. The second column shows all the results of the descriptive coding. The third column shows the result of the interpretive coding, and in the fourth column, the table shows the categorization into the motivation type.

Data examples	Descriptive coding	Interpretive coding	Motivation type
"Online ads make me feel emotionally drained."	Ads are exhausting	Reduced well-being through mobile ads	Intrinsic motivation
"In my opinion, online advertising is simply disturbing, and I feel fatigued when being exposed to ads over a longer period of time."	Advertising fatigue		
"Actually, online ads annoy me so much that I just want to get rid of them. That's why I would use an ad-blocker."	Annoyance of ads		
"Being exposed to ads all day is really a strain for me."	Advertising is stressful		
"One of the main reasons why I intend to use a mobile ad-blocker is that all tracking scripts are disabled."	Tracking disabled	Improved privacy protection	Intrinsic motivation
"They tack your search and browsing history through all the online ads,[…] and if you block the ads, it is harder for them to trace you."	No search history		
"Ad-blockers enable you to protect your privacy."	Enables privacy		
"I guess ad-blockers protect your private data better than if you use just a normal browser."	Privacy is better protected		
"I would use an ad-blocker because ad-blockers minimize the threat of getting infected by malicious code or the like."	No malicious code	Improved security	Extrinsic motivation
"If you don't get the bad ads, you probably don't get a virus."	No viruses		
"Blocking ads would also mean blocking all the malicious code contained in some ads."	Helps to block viruses		
"The nice thing about ab-blockers is that you can use websites instantly without having to see any ads."	No ads displayed	Improved user experience	Extrinsic motivation
"I go on websites to get information and not to see online ads […] without ads some website would be more useful to get information."	Increased usability		
"With an ad-blocker, there would be no more disruption of those online ads."	No disruption anymore		
"Ad-blockers remove all those fancy ads, which would lead a clean design of the websites [...] would be a way better experience."	Clean websites		
"I guess it would be comfortable to surf without the online ads."	Increases comfort		
"No ads through an ad-blocker would mean that I do not get irritated by ads."	Less irritation		
"Using an ad-blocker would significantly reduce page loading time. That is why I intend to use an ad-blocker."	Reduces loading time	Increased performance	Extrinsic motivation
"Ads slow down the load time of websites […] with an ad-blocker, I hope to get a faster surfing experience."	Faster surfing		
"A clear benefit of ad-blocker would be the faster loading of websites."	Website loads faster		

"The point is, I don't know how this all works or even how to install an ad-blocker. So, I do not really intend to use an ad-blocker."	Complicated to install	Perceived mobile incompetence	Amotivation
"I can do the basic things with a smartphone, but not more."	Not mobile affine		
"I do not know where to get an ad-blocker or even how to load it onto my phone."	Lack of knowledge		
"That's all so difficult, and I just know so little about that."	Lack of expertise		
"When mobile websites offer service for free, I believe that displaying mobile ads for financing the service is appropriate, and so, I would not use a mobile ad-blocker."	Free content in return	Perceived reciprocity	Amotivation
"I think that many websites have to show ads or otherwise they could not operate on a free basis."	Understanding of the online ecosystem		

Table 7. An Example of the Coding Procedure (following Myers (2019))

APPENDIX D: CONSTRUCT MEASURES

Table 9 contains the constructs and items we used in the 249 surveys with current non-users of mobile ad-blockers. Additionally, we display the item loadings.

Improved user experience — adapted from Zhang et al. (2011) I expect that using a mobile ad-blocker will make websites more user-friendly. [0.874] I expect that using a mobile ad-blocker will make websites easier to use. [0.895] I expect that using a mobile ad-blocker will make websites better organized. [0.762]
Increased performance — adapted from Wells et al. (2011) I expect that when I use the web, using a mobile ad-blocker will reduce the waiting time between my actions and the website's response. [0.825] I expect that using a mobile ad-blocker will make websites load quicker. [0.965] I expect that using a mobile ad-blocker will make websites take less time to load. [0.886]
Improved privacy protection — adapted from Tucker (2014) I expect that using a mobile ad-blocker will increase the protection of my personal. [0.886] I expect that using a mobile ad-blocker will increase the protection of my Internet data. [0.961] I expect that using a mobile ad-blocker will increase the protection of my Internet privacy. [0.933]
Improved security — adapted from Johnston and Warkentin (2010) I expect that using a mobile ad-blocker will decrease the risk of getting infected with spyware. [0.982] I expect that using a mobile ad-blocker will decrease the risk that my mobile device becomes infected with spyware. [0.983] I expect that using a mobile ad-blocker will decrease the possibility that my mobile device will get infected with spyware. [0.924]
Reduced well-being through mobile ads — adapted from Moore (2000) I feel emotionally drained from browsing websites with many ads. [0.882] I feel used up while browsing websites with many ads. [0.882] I feel fatigued while browsing websites with many ads. [0.883] I cannot continue browsing websites with many ads for very long periods at a time. [0.708] I feel burned out from browsing websites with many ads. [0.894] Being exposed to ads all day is really a strain for me. [0.843]
Perceived mobile incompetence — adapted from Wei et al. (2011) I am not confident in how to install and configure a mobile ad-blocker. [removed] I have difficulties following instructions to install and configure a mobile ad-blocker. [0.772] I feel uncomfortable installing and configuring a mobile ad-blocker on my own. [0.906] I am not sure I can install and configure a mobile ad-blocker. [0.915] I cannot install and configure a mobile ad-blocker if no one tells me how to do it. [0.762]
Perceived reciprocity — adapted from Schumann et al. (2014) When mobile websites offer service for free, I believe that displaying mobile ads for financing the service is appropriate. [0.883] I accept mobile ads in return for free access to the mobile website. [0.927] It is fair that mobile websites show mobile ads in return for providing free content to me. [0.920] It is okay that mobile websites show mobile ads in exchange for free content. [0.849] Having mobile ads in return for free content is fair [0.836].
Intention to use — adapted from Hong and Tam (2006) I intend to use a mobile ad-blocker in the future. I expect that I will use a mobile ad-blocker in the future. I am considering using a mobile ad-blocker in the future.
Note: All items were measured on a 7-point Likert agreement scale ranging from 1 = ‘completely disagree’ to 7 = ‘completely agree.’ Figures in brackets show the loading.

Table 9. Information on construct measures

Paper IV

The Dark Side of Remote Work:

A Mixed-Methods Study on Remote Work Stress

Lea Reis
University of Bamberg

Christian Maier
LMU Munich School of Management, Ludwig-Maximilians-Universität München

Felicitas Beer
University of Bamberg

Tim Weitzel
University of Bamberg

Submitted version.

The Dark Side of Remote Work: A Mixed-Methods Study on Remote Work Stress

ABSTRACT

Should organizations offer employees the possibility of permanently working from home, even though it burdens their mental health? We apply a mixed-methods approach with two studies to take a stress-theoretic perspective on the adverse effects of remote work. Study 1 uses 22 semi-structured interviews to identify remote work stressors and adverse consequences for employees affecting organizations. We identified six remote work stressors, three immediate remote work consequences, and two long-term remote work consequences. The results inform Study 2 by developing a research model. This research model is validated with a quantitative study using survey data (N=131 remote workers). Our results show that remote work stressors affect employees' well-being, organizational commitment, and perceived job performance. We contribute to remote work research and research on work and remote work stress.

Keywords: Telework; virtual work; social isolation; well-being; job performance; organizational commitment

1 INTRODUCTION

Flexible working arrangements like working from home have gained momentum in the fight for young talents and knowledge workers (Kelly 2021). Recent statistics show that, due to the experienced benefits of flexibility, 85 percent of candidates only want to apply for remote flexibility jobs, and 30 percent would ‘absolutely not’ apply for a full-time, on-site job (Oliveros 2021). In the same vein, two out of three employees state that working from home also has drawbacks. These drawbacks include increased isolation, loneliness, and difficulty disconnecting from work (Robinson 2021), burdening mental health. These conflicting effects put organizations in the difficult situation of balancing the risk of losing or not being able to recruit employees by cutting working-from-home opportunities on the one hand (Oliveros 2021) and the risk of losing employees due to mental health conditions associated with working from home, on the other hand (Robinson 2021). To make a profound decision, organizations must understand the effects of remote work to assess the consequences for themselves and their employees.

Working from home, typically known as remote work or telework, has two characteristics: the use of information and communication technologies (ICTs) while working and the physical separation from the conventional workplace (Carillo et al. 2021). Early research has primarily stressed the benefits of not working on-site, like increased flexibility, productivity, job satisfaction, and saving office space (e.g., Bélanger et al. 2001; Igbaria and Guimaraes 1999). More recent research focuses on the adverse issues related to remote work (e.g., Golden et al. 2008), including difficulties in career advancement (Gajendran and Harrison 2007), increased social and professional isolation (Golden et al. 2008; Mulki and Jaramillo 2011) less social contacts with colleagues (Bloom et al. 2015), or reduced organizational commitment (Baruch 2000).

Research agrees that a stress-theoretic perspective helps understand these issues (Saura et al. 2022; van Zoonen et al. 2021) and shows that remote workers are more likely to deal with stress-related symptoms affecting mental health than employees working on-site (Mann and Holdsworth 2003). Concerning this stress-theoretic perspective, research has identified that working on-site and remotely can be stressful and adversely affect employees and organizations (Maier et al. 2015; Saura et al. 2022). So far, existing works primarily use the perspective of work stress and related work stressors (Ahuja et al. 2002) to explain remote work stress and ignore the specific stimulating demands related to the particular characteristics of remote work, so remote work stressors, such as imminent isolation (Golden et al. 2008). The simple transfer from existing stressors and their adverse consequences identified in literature treating work stress (Ahuja et al. 2007) to remote work stress provides only a limited explanation of the influence of those specific remote work characteristics on employees' perceived remote work stress. However, recent literature shows that these particular characteristics are essential to understanding the effects of remote work on employees (Carillo et al. 2021; Waizenegger et al. 2020). Given the importance of specific remote work characteristics (Golden et al. 2008), we need to identify specific remote work stressors and adverse consequences to understand the effects on employees and organizations. Taking that opportunity, we ask the following research question:

Which specific remote work stressors and associated adverse consequences exist, and how do they affect employees working from home?

To answer the research question, we follow a mixed-methods approach. Study 1 uses 22 semi-structured interviews to identify remote work stressors and associated adverse consequences affecting remote employees. We identified six remote work stressors that evoke adverse consequences for employees. The results inform Study 2 by developing a research model. This research model is validated with a quantitative study using survey data (N=131 remote workers). Our results show that remote work stressors affect employees' well-being, organizational commitment, and perceived job performance. We contribute to remote work research and research by treating work and remote work stress with our results.

2 THEORETICAL BACKGROUND

This section discusses related research on remote work and then outlines the theoretical concepts of remote work stress.

2.1 Remote Work

There is no clear consensus on the definition of working from home, also called remote work or telework, across academic fields (Carillo et al. 2021). Still, most definitions incorporate two characteristics: 1) using ICTs for work and 2) the physical separation from the conventional workplace. The role of ICTs for remote work differs from ICTs as a tool to stay connected with others that allows distance from the workplace (Bélanger and Allport 2008) to ICTs used to restructure the way of working remotely (Baker et al. 2006). Remote work is associated with various benefits for employees and organizations. Employees tend to complete tasks more efficiently due to fewer distractions, contributing to organizations' productivity (Bloom et al. 2015). Remote work comes with high flexibility in working hours (Suh and Lee 2017) and a better integration of work and private life (Allen et al. 2021), which enables equal chances for men and women to develop careers through a better balance of family and job demands (Greenhill and Wilson 2006). The increased autonomy and trust expressed through the possibility of working from home increases employees' job satisfaction (Waizenegger et al. 2020), resulting in less job fluctuation (Igbaria and Guimaraes 1999). In contradistinction, literature has identified various drawbacks related to remote work, such as constant connectivity to work in non-work hours (Derks et al. 2016) and the pressure to reply to demands (Matusik and Mickel 2011). Further, employees simultaneously experience the emotionally demanding proximity of home and work, leading to fatigue, negative emotions (Sonnentag et al. 2008), and a constant distraction from private life and family (Allen et al. 2015).

With the outbreak of the COVID-19 pandemic, the role of remote work has suddenly changed from a privilege offered by employers to their employees to a way to ensure business continuity in times of home confinement (Carillo et al. 2021). Pandemic-induced remote work has inherent specificities and work-environment particularities linked to its implementation and the surrounding crises (Carillo et al. 2021; Waizenegger et al. 2020). Remote work has become a mandatory full-time practice with permanent physical separation from the conventional workplace, which has occurred suddenly and unpreparedly (Carillo et al. 2021). With the voluntary nature of remote work no longer being fulfilled, many advantages of remote work, such as the high autonomy and flexibility of working hours (Suh and Lee 2017), are restricted. Instead, employees have to deal with mock-up workspaces at home, new working routines, potentially new ICTs, and professional and private time balancing issues, adding to the identified drawbacks of remote work (Carillo et al. 2021; Waizenegger et al. 2020). General work stress literature shows that such circumstances can adversely affect employees' well-being, such as exhaustion (Moore 2000), grounded in stress (Ahuja et al. 2007). To better understand the adverse consequences of remote work on employees' well-being, respecting the importance of the specific remote work characteristics, we next outline an overview of how stress is affiliated with remote work.

2.2 Literature on Stress in General and Remote Work Stress in Particular

Stress is a transactional process that translates demanding stimuli, called stressors, into adverse consequences (Lazarus and Folkman 1984) and offers a valuable perspective to explain the adverse consequences of remote work (van Zoonen et al. 2021). Literature shows remote workers are more likely to deal with stress-related mental health symptoms than on-site employees (Mann and Holdsworth 2003). This fact could be related to specific characteristics that come with not working on-site, such as increased social and professional isolation (Golden et al. 2008; Mulki and Jaramillo 2011) and less social contact with colleagues (Bloom et al.

2015), stressing employees (Saura et al. 2022). Over the last few years, research has dug deeper into the relationship between remote work and stress (Adamovic 2022; van Zoonen et al. 2021). However, while those works prove that remote work is stressful, those works have not considered or identified specific remote work stressors or associated adverse consequences explaining remote work stress. Instead, they rely on related research streams treating work stress (Ahuja et al. 2002) or stress related to ICT use (van Zoonen et al. 2021) and offer various explanations for the accumulation of stress-related symptoms among remote workers. One explanation compromises the simultaneous influence of work stressors and stressors related to ICT use (Maier et al. 2015) that rise from the necessity to use ICTs while working remotely and contribute to exhaustion (Ayyagari et al. 2011; Moore 2000; Podsakoff et al. 2007). Other explanations affiliate employees' stress perception primarily to work stressors, such as work overload, role overload, or work-home conflict, and work-stress-related consequences, such as work exhaustion or lowered satisfaction, organizational commitment, and performance (Ahuja et al. 2002; Golden et al. 2008), holding for remote and on-site work (Ahuja et al. 2007). Still, the simple transfer from existing work stressors and their adverse consequences identified in literature treating work stress (Ahuja et al. 2007) to the context of remote work provides only a limited explanation of the influence of specific remote work characteristics, such as imminent isolation (Golden et al. 2008), on employees and their perceived remote work stress. However, those specific characteristics shaping remote work are particularly important to understand the effect on and consequences for employees (Carillo et al. 2021). For example, existing research indicates an influence of the time spent working remotely on employees' perceptions of adverse effects related to remote work (Golden et al. 2008). These findings could also indicate that some perceived stressors and associated adverse consequences intensify or lower their influence with increased endurance of remote work. Other research shows that the characteristics and circumstances of pandemic-induced remote work differ from pre-pandemic remote work, as working from home has lost its voluntary character and become a mandatory full-time practice (Carillo et al. 2021; Waizenegger et al. 2020). Those changes could also influence how employees perceive remote work stressors and associated adverse consequences, contributing to an increasing perception of stress related to remote work since the pandemic (Saura et al. 2022). Current literature cannot answer those questions as they neither consider nor identify specific remote work stressors and associated adverse consequences that capture the specific characteristics of remote work. We conducted a mixed-methods approach, combining one qualitative and one quantitative study, to identify specific remote work stressors and associated adverse consequences that add to the understanding of remote work stress. We will elaborate on our mixed-methods approach next.

3 MIXED-METHODS APPROACH

We follow a developmental mixed-methods approach (Venkatesh et al. 2013) consisting of two equally weighted studies. The qualitative study (Study 1) aims to identify remote work stressors and associated adverse consequences. The quantitative study (Study 2) empirically validates the developed remote work stress research model. Within our sequential, partially mixed, multi-strand design, we use the results of Study 1 to inform Study 2 (Table 1).

	Study 1	**Study 2**
Characterization:	qualitative	quantitative
Methodology:	qualitative interviews	structural equitation modeling
Data Collection:	22 semi-structured interviews with white-collar workers	131 quantitative surveys based on the input of Study 1
Analysis:	descriptive/interpretative coding	structural and measurement model
Purpose:	identifying remote work stressors and adverse consequences, developing a research model	empirical validation of the research model

Table 1. Mixed-Methods Approach

3.1 Study 1: Identifying Remote Work Stressors and Associated Adverse Consequences

3.1.1 Data Collection

We first aim to identify remote work stressors and associated adverse consequences. So, we conducted 22 semi-structured interviews with white-collar workers in *Anonymous*[13] who worked exclusively from home for at least nine months during the COVID-19 pandemic. The participants' ages ranged from 23 to 55, with 80 percent of the participants younger than 36. Within our sample, we had an equal distribution of biological sexes. All participants had, on average, 8.75 years of working experience and used ICTs for more than 85% of their workday. Due to the restrictions of social distancing in autumn 2021, we invited the participants to virtual meetings and recorded the session with the permission of each participant. The interviews lasted, on average, 45.3 minutes and followed a semi-structured guideline (see Appendix for details). We asked the participants about their experiences working from home during the pandemic, specifically whether their routines had changed compared to working on-site. Further, we asked about challenging experiences and demanding stimuli, focusing on their social work environment, working conditions, and organizational support to help them succeed

[13] Country anonymized for review purposes

in those challenges. Last, we asked about the influence of the pandemic on their working routines and perceived job performance.

3.1.2 Data Analysis

Following a coding scheme, we coded all interviews with MAXQDA 2020 (Myers 2019). We first identified the statements describing remote work stressors and associated adverse consequences. Then, we used descriptive coding (62 codes) and interpretative coding (12 codes) to summarize similar statements. Last, we categorized the coded statements into remote work stressors and immediate and long-term adverse consequences. To ensure objectivity, two research team members coded the items independently. We provide a coding example in the Appendix.

3.1.3 Validation

Following examples in research, we discussed the validity of our data collection and analysis in several categories. We assured *design validity* by applying an appropriate method to identify remote work stressors and associated adverse consequences, attesting to descriptive validity. We also collected data from a sufficiently large sample (Collins et al. 2006) from a representative population to ensure credibility, transferability, and transparency in our data collection. Regarding *analytical validity*, we designed our interviews based on well-established frameworks (Ahuja et al. 2007) to reach a certain plausibility and theoretical validity. The questions have been pretested with students to eliminate wording inconsistencies or comprehension problems. We recorded and transcribed all questions and answers exactly and completely. Concerning *inferential validity*, we asked participants for feedback on our understanding of their answers, and we attempted to understand their descriptions and feelings. We coded the data very close to the answers given. We cross-checked our coding with the research team to confirm their validity.

3.1.4 Results

Conducting the interviews, we understand that employees are exposed to various stressors that yield adverse consequences. We provide definitions of the identified constructs in Table 2. Some consequences reveal themselves within a short time spent working remotely, which we label as *immediate remote work consequences*. After working remotely for approximately six months, additional adverse consequences occur, which we label as *long-term remote work consequences*.

Category	Construct	Definition
Remote work stressors	Role conflict	The degree to which an individual is exposed to contradictory, incompatible, or incongruent role requirements while working remotely (adapted from Ahuja et al. (2007)).
	Reduced communication quality	The degree to which communicating through digital technologies while working remotely reduces the openness and quality of interpersonal communication (adapted from Lowry et al. (2009)).
	Lack of appreciation	The degree to which individuals feel like they lack opportunities for development and appreciation for their work while working remotely (adapted from Tourangeau and McGilton (2004)).
	Lack of perceived organizational support	The degree to which an individual feels they lack technical, social, and furniture-related support from their organization while working remotely (adapted from Farh et al. (2007)).
	Lack of contact with supervisor and co-workers	The degree to which individuals feel they lack personal interaction with and feedback from their supervisor and co-workers while working remotely (adapted from Rosen et al. (2006)).
	Role overload	The degree to which the requirements of individuals' roles exceed their capacity in terms of the level of difficulty or the amount of work while working remotely (adapted from Jones et al. (2007))
Immediate remote work consequences	Fear of rejection	The degree to which individuals feel threatened to be rejected by their co-workers and supervisor for inadequate communication and behavior while working remotely (adapted from Lemay and Clark (2008)).
	Job satisfaction	The degree to which an individual feels pleased or content with their job or job experiences due to working remotely (adapted from Ahuja et al. (2002)).
	Work exhaustion	The degree to which an individual feels physically, emotionally, and mentally exhausted from working remotely (adapted from Moore (2000)).
Long-term remote work consequences	Organizational commitment	The degree to which an individual agrees with an organization's home office policies and desires to engage for the organization (adapted from Bozeman and Perrewé (2001)).
	Perceived job performance	The degree to which an individual feels productive while working remotely (adapted from Golden et al. (2008)).

Table 2: Definition of Constructs

Our data analysis discloses six remote work stressors: *role conflict*, *reduced communication quality*, *lack of appreciation*, *lack of perceived organizational support*, *lack of contact with supervisors and co-workers*, and *role overload*. Additionally, we identified three immediate remote work consequences: *fear of rejection,* negative effects on *job satisfaction and work exhaustion*, and two long-term remote work consequences, namely negative effects on *organizational commitment* and *perceived job performance*.

3.2 Research Model and Hypotheses Development

The purpose of Study 1 is to inform the development of a research model capturing remote work stressors and associated adverse consequences based on the identified constructs (see Figure 1). Building on our interviews and existing literature (Ahuja et al. 2002), we hypothesize that the identified remote work stressors yield specific immediate and long-term remote work consequences.

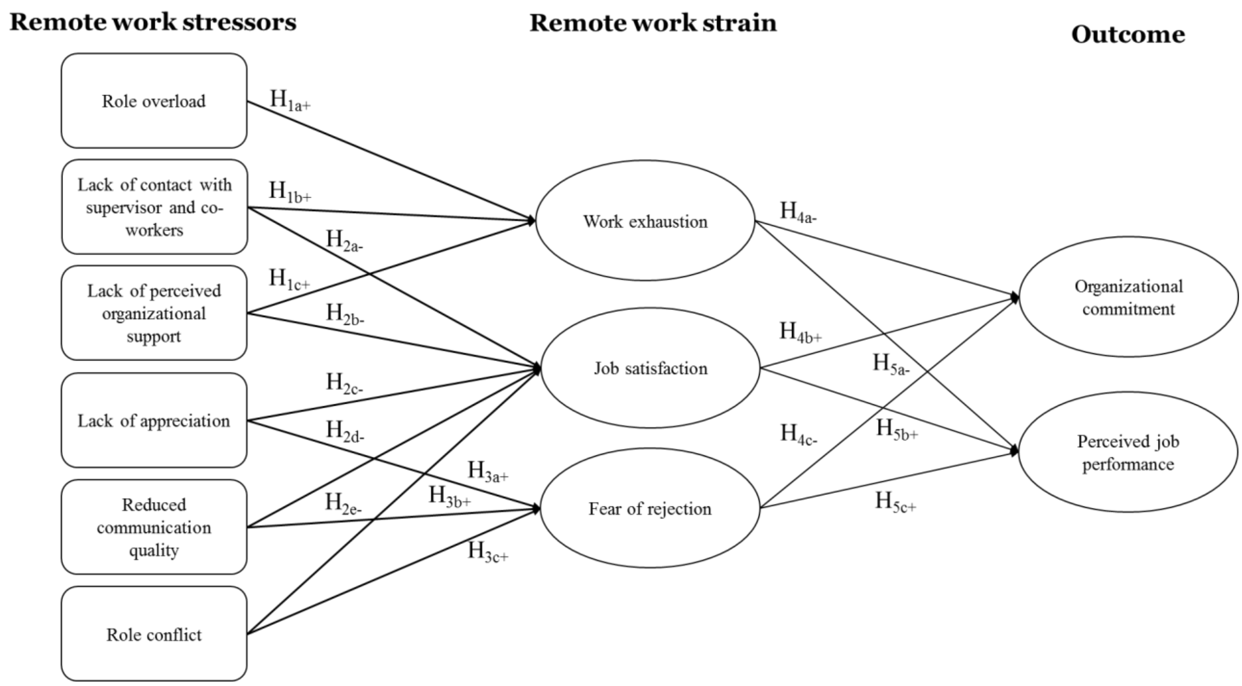

Figure 1. Research Model and Hypotheses

Literature shows that handling excessive tasks while working can lead to exhaustion (Moore 2000). This finding is congruent with our interviews, where employees stated that they feel drained by the work they have to handle while working remotely. The lack of communication with co-workers or supervisors also necessitates more coordinated meetings, contributing to the feeling of being exhausted (Ahuja et al. 2007). This fact leads to compensation for this lack of time by working overtime and reducing their breaks, which further blurs the boundaries between their work and private lives, which they have to handle without the support of their organizations. It causes emotional, physical, and mental exhaustion (Moore 2000). We hypothesize that

H_1: Role overload (H_{1a}) lack of contact with supervisors and co-workers (H_{1b}), and lack of perceived organizational support (H_{1c}) positively influence work exhaustion.

Being exposed to poor communication, description of work, and feedback can lower employees' satisfaction with their jobs due to being poorly integrated into the team (Golden et al. 2008). Apart from increased difficulty in forming new relationships with colleagues and supervisors, remote workers can feel unsupported in handling the challenges of remote work by the organization. Professional isolation results in poor embeddedness into team structures, social groups, or the organization (Golden et al. 2008; Mulki and Jaramillo 2011), leading to lower job satisfaction because of reduced quality of information compared to socially integrated workers. Therefore, we hypothesize that:

H_2: Lack of contact with supervisors and co-workers (H_{2a}), lack of perceived organizational support (H_{2b}) lack of appreciation (H_{2c}), reduced communication quality (H_{2d}) and role conflict (H_{2e}) negatively influence job satisfaction.

Our interviews suggest that when working remotely, employees perceive no clear guidelines regarding virtual communication and a lack of social cues, such as body language or intonation, especially in written communication or non-video calls. Literature also indicates that virtual communication is less rich in social cues and less informative concerning implicit or timely knowledge (Sardeshmukh et al. 2012), making it difficult for employees to interpret information correctly and bond on a social level (Lowry et al. 2009). The reduced communication quality and role conflict lead to particular insecurity in social contexts (Sardeshmukh et al. 2012). Further, employees perceive a lack of transparency regarding their performance and the recognition of that performance from supervisors and co-workers. Receiving less feedback on achievement and professional development opportunities creates social insecurity (Sardeshmukh et al. 2012). We hypothesize that role conflict, reduced communication quality, and the lack of appreciation from co-workers and supervisors positively influence employees' fear of rejection for inadequate communication and behavior while working remotely.

H_3: Lack of appreciation (H_{3a}), reduced communication quality (H_{3b}), and role conflict (H_{3c}) positively influence employees' fear of rejection.

According to the interviews and existing literature (Ahuja et al. 2002), job satisfaction positively affects organizational commitment, fostering the wish to stay in the organization. Work exhaustion negatively influences organizational commitment. The poor emotional and cognitive state associated with work overload requires a change of the outer circumstances, often resulting in turnovers (Moore 2000). Further, the fear of rejection decreases employees' identification with their team and the organization, decreasing loyalty toward their employer (Lemay and Clark 2008). We hypothesize that

H_4: Work exhaustion (H_{4a}) and fear of rejection (H_{4c}) negatively influence organizational commitment, while reduced job satisfaction (H_{4b}) positively influences it.

Literature shows that job satisfaction is positively related, and perceived work exhaustion is negatively associated with lower productivity (Moore 2000). However, in line with the literature (Bloom et al. 2015), most of the interviewed employees are convinced of increasing their perceived productivity while working remotely due to their ability to work unlimited hours without interruption, even in case of sickness or during meetings. This behavior stems from a fear of rejection. We hypothesize that their extra work compensating for their fear of rejection increases their perceived job performance.

H_5: Fear of rejection positively influences perceived job performance (H_{5c}), while reduced job satisfaction (H_{5b}) and work exhaustion (H_{5a}) negatively impact perceived job performance.

3.3 Study 2: Empirical Validation of our Research Model

3.3.1 Data Collection

To empirically validate our research model on remote work stress, we prepared a quantitative survey distributed among white-collar workers who exclusively worked from home for at least nine months of the pandemic. We chose this sampling strategy because our interviews indicated that there had been long-term remote work consequences after six months of remote work. Participants from the interviews could not participate in our quantitative study. To ensure that all participants suited our sampling strategy, we included a screening question ('Do you work or have you worked remotely permanently during the pandemic (for at least nine months)?'). Further, we included attention tests to increase data quality (Lowry et al. 2016). In total, 237 employees participated in the survey, from which we excluded 106, as they did not work remotely for more than nine months. The final data set consists of 131 surveys. The participants' ages ranged from 23 to 65, with 60 percent of the participants younger than 36. Within our sample, we had an equal distribution of biological sexes. On average, all participants had 12 years of working experience and used ICTs for more than 90% of their workday. Prior research (Podsakoff et al. 2003) shows that self-reported data could imply common method bias (CMB). We paid special attention to the set-up of our survey to avoid CMB and conducted two statistical analyses to identify the extent of CMB. First, Harman's single-factor test indicates whether the majority of the variance can be explained by one single factor. The examination reveals that only 24 percent can be explained by one factor below the 50 percent threshold (Podsakoff et al. 2003). Second, we added a CMB factor into the PLS model (Podsakoff et al. 2003; Williams et al. 2003) that contains every indicator of the original model. We transformed the remaining original factors into single-item constructs. Next, we compared the coefficient of determination (R2) ratio with the CMB factor to R2 without the CMB factor. As the method factor explains a delta of R2 of 0.006 and R2 without this factor of 0.683, we got a ratio of 1:114. Comparing this ratio with the percentages reported in prior research investigating CMB, we can state that CMB does not significantly influence our results (Liang et al. 2007).

3.3.2 Measurement Model and Validation

		Mean	SD	AVE	CR	α	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Role conflict	3.311	1.267	0.577	0.803	0.714	0.759										
(2)	Reduced communication quality	2.930	1.083	0.651	0.882	0.821	0.352	0.807									
(3)	Lack of appreciation	3.408	1.359	0.716	0.882	0.797	0.418	0.425	0.846								
(4)	Lack of perceived organizational support	3.109	1.143	0.688	0.869	0.774	0.290	0.384	0.479	0.830							
(5)	Lack of contact with supervisor and co-workers	4.129	1.505	0.653	0.882	0.822	0.560	0.435	0.497	0.260	0.808						
(6)	Role overload	4.266	1.5330	0.739	0.894	0.823	0.331	0.265	0.232	0.187	0.435	0.860					
(7)	Fear of rejection	2.161	1.016	0.802	0.924	0.877	0.496	0.335	0.351	0.264	0.375	0.322	0.896				
(8)	Job satisfaction	5.229	1.098	0.826	0.934	0.894	-0234	-0.497	-0.619	-0.496	-0.500	-0.258	-0323	0.889			
(9)	Work exhaustion	3.834	1.607	0.751	0.938	0.917	0.497	0.334	0.493	0.402	0.673	0.586	0.324	-0541	0.867		
(10)	Organizational commitment	5.416	1.258	0.556	0.834	0.736	-0.223	-0371	-0.460	-0.586	-0.422	-0.218	-0.340	0.592	-0.430	0.746	
(11)	Perceived job performance	4.655	1.502	0.761	0.927	0.896	-0.231	-0.268	-0.359	-0285	-0.405	-0.293	-0.187	0.387	-0.552	0.190	0.872

Note: square root of AVE is listed on the diagonal of bivariate correlations; SD = standard deviation; α = Cronbach's alpha; AVE = average variance extracted; CR = composite reliability;

Table 3. Descriptive Statistics and Discriminant Validity

We assured the validity of our measurement model (Table 3) using the following key values. The AVE of each construct is higher than 0.50, and Cronbach's alpha and the CR for each construct are higher than 0.70, which attests to construct reliability. We can ensure discriminant validity as the square root of the AVE is higher than the corresponding correlations of the constructs (Fornell and Larcker 1981; Hulland 1999). Furthermore, we calculated a heterotrait-monotrait (HTMT) ratio of 0.77, lower than the absolute HTMT0.85 criterion (Henseler et al. 2014b), and therefore attests to discriminant validity. Those thresholds indicate that our measurement model is valid.

We assured *design validity* by using the results of Study 1 for Study 2. Further, we collected data from a sufficiently large sample (Collins et al. 2006) from a representative population to ensure credibility, transferability, and transparency in our data collection. We measure each construct in the proposed research model with reflective indicators, so we focus on content validity, indicator reliability, construct reliability, and discriminant validity to ensure the validity of the measurement model (Bagozzi 1979). We base all measures on existing ones validated and used by previous research to ensure content validity (see Appendix). Concerning *inferential validity*, we followed the rules of path analysis (Hair et al. 2017).

3.3.3 Data Analysis and Results

We base on structural equitation modeling (SEM) and analyze the results following the partial least squares (PLS) method and SmartPLS 3.2.8 (Ringle et al. 2014). Our structural model (see Figure 2) shows that eleven out of 17 hypotheses are significant, except for H_{3a}, H_{3b}, H_{4a}, H_{4c}, H_{5b}, and H_{5c}. Our model explains 28.7 percent of fear of rejection, 53.8 percent of job satisfaction, 60.2 percent of work exhaustion, 38.6 percent of organizational commitment, and

31.6 percent of perceived job performance. The standardized root mean square residual (SRMR) is 0.078, below the 0.08 threshold, indicating a good model fit (Bentler and Bonett 1980; Henseler et al. 2014a). Demographic controls, such as age, gender, and work experience, did not reveal significant influences on our dependent variables.

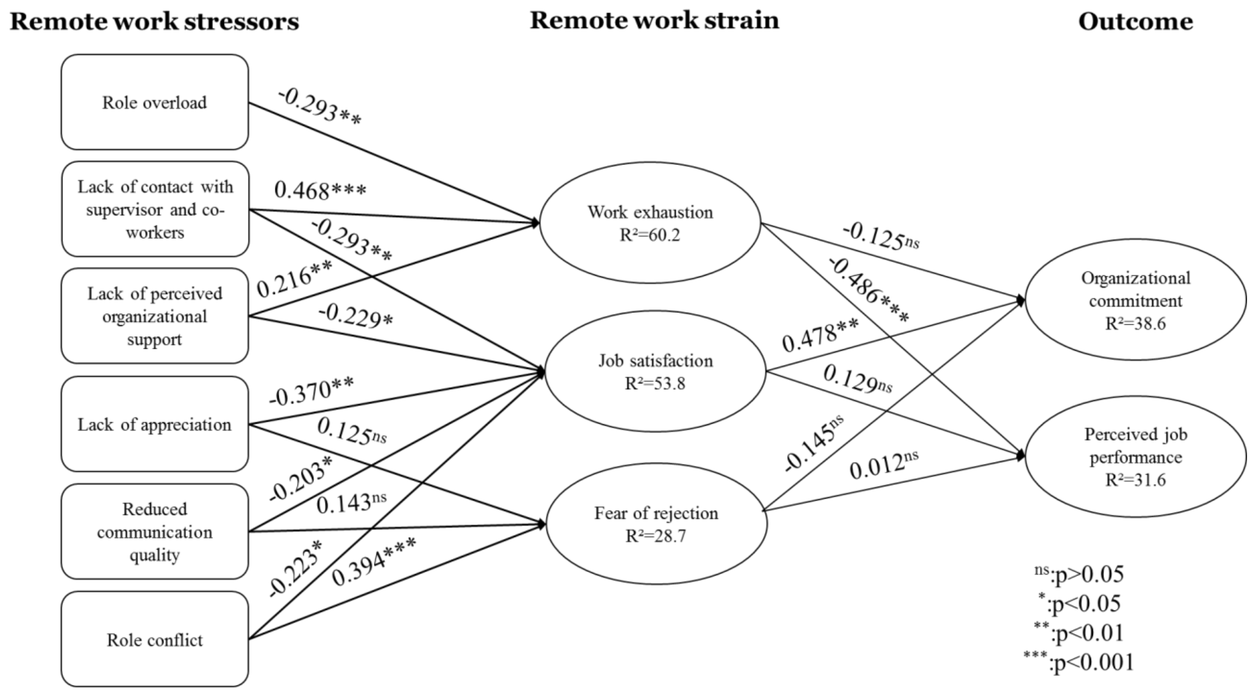

Figure 2. Structural Model

3.4 Meta-Inferences

Our developmental mixed-methods approach aimed to build and validate our remote work stress model. Therefore, we combined one qualitative and quantitative study to yield insights beyond the individual study results, called meta-inferences (Venkatesh et al. 2013). We present both studies' convergent, divergent, and complementary results hereafter.

Study 1 revealed six remote work stressors, three immediate remote work consequences, and two long-term remote work consequences. Our quantitative results confirm that all identified stressors contribute to those adverse consequences. Further, most hypotheses are significant. Therefore, we can deduce that the specified model is validated.

Concerning divergent results, we see that fear of rejection does not significantly influence the identified long-term remote work consequences of reduced organizational commitment and perceived job performance. This finding contradicts our qualitative results, indicating that fear of rejection from co-workers and supervisors is a social driver of reduced organizational commitment and lower perceived job performance. Our interviews suggest that the fear of rejection causes changes in behavior, such as being super appreciative of little support indicating social acceptance or trying to earn social acceptance through outstanding work. This fact could explain why the relationships here are not significant. There are also cases in which fear of rejection contributes to an over-commitment of the organization and an extra highly perceived job performance, depicting an asymmetric relationship.

Additionally, work exhaustion has no significant negative effect on organizational commitment. This result indicates that the employees do not relate their excessive emotional and cognitive engagement for work with the employer's policies. Last, job satisfaction has no significant influence on perceived job performance, which could be explained by the interview finding that some interviewees do not connect their performance to their satisfaction, and unsatisfied employees sometimes overrate their performance. We ensure the quality of our meta-inferences regarding design validity, as we validated both individual studies and explanation quality, combined both results and tried to explain the inconsistencies.

4 DISCUSSION

Organizations have to face the challenging decision of offering their employees working-from-home opportunities that, on the one hand, are desired by most employees (Oliveros 2021) and, on the other hand, can burden employees' mental health (Robinson 2021). Building upon a stress-theoretic perspective (Lazarus and Folkman 1984), we identify remote work stressors and adverse immediate and long-term remote work consequences. Our results indicate that remote work stressors can yield adverse consequences regarding work exhaustion, job satisfaction, and the fear of rejection, eventually influencing employees' organizational commitment and perceived job performance. This result is an essential insight for organizations, as they need to deal with the issue of remote work stress to avoid losing employees due to burnout or turnover (Ahuja et al. 2002; Maier et al. 2015; Zaza et al. 2022). We will outline our contributions hereafter.

4.1 Theoretical Contributions and Practical Implications

Over the last few years, research has increasingly treated the relationship between remote work and stress (Adamovic 2022; van Zoonen et al. 2021). However, those works have not considered or identified specific remote work stressors or associated adverse consequences. Still, they rely on related research streams treating work stress (Ahuja et al. 2002) or stress related to ICT use (van Zoonen et al. 2021) to explain remote work stress.

We complement those insights by offering a remote work stress model conceptualizing the specific characteristics of remote work stress, the involved stressors, and adverse consequences. Our model consists of six remote work stressors, from which three, namely role conflict, lack of contact with co-workers and supervisors, and role overload, have already been treated in general work stress research (Ahuja et al. 2007; Moore 2000). With reduced communication quality, lack of appreciation, and lack of organizational support, we offer three remote work stressors beyond existing insights that help us understand remote-working employees' specific demands. Further, while work exhaustion and job satisfaction are well-researched consequences of work stress (Moore 2000), with fear of rejection, we offer a specific consequence of remote work stress, referring to the potential of social separation resulting from isolation. Together with the identified remote work stressors, we show that this fear adds to the social aspects of remote work stress beyond the identified issues of role conflict and lack of contact, also applying to on-site work (Moore 2000). The additional identified stressors and fear of rejection could explain why remote workers are more likely to deal with stress-related mental health symptoms than on-site employees (Mann and Holdsworth 2003). Our interviews characterize fear of rejection, reduced job satisfaction, and increased work exhaustion as immediate remote work consequences that yield further long-term consequences after a more extended period of remote work. Those long-term consequences, the reduced organizational commitment, and perceived job performance are known from remote stress research involving stressors from work stress research (Ahuja et al. 2002). We add to the understanding of those constructs by adding antecedents regarding remote work stressors and immediate remote work consequences. These findings contribute to understanding how remote work stress occurs and which stressors and adverse consequences are involved.

Concerning the effects of the stressors, remote work literature suggests that the work stressors of role conflict and role overload decrease with a greater extent of remote work (Sardeshmukh et al. 2012). However, our interviews suggest that this is not the case with full-time remote work. On the contrary, our interviews show that the permanent physical separation from the conventional workplace creates additional adverse, mainly social, effects that intensify with the increasing duration of the separation. The interviews suggest that the more time employees spend isolated working from home, the less they can define and identify with their fundamental role within the organization, contributing to the fear of rejection (H_{3c} also quantitatively validated, 0.394, $p<0.001$). This conflicting finding adds to remote work research (Carillo et al. 2021; Waizenegger et al. 2020) by elaborating on the differing influence of full-time remote work on remote work stress.

Concerning practical implications, our results indicate that remote work stress can reduce employees' organizational commitment, putting organizations at risk of losing employees (Ahuja et al. 2002). We recommend that organizations actively work on their remote work communication policy to avoid those consequences. Many employees want explicit guidelines for using particular tools and best practices for communication in remote work. Those guidelines include the commitment to using videos during video calls, regular coffee chats with other employees and supervisors, feedback mechanisms, and the extra effort to add social information to the communication that cannot be transmitted via video-supported or written conversation. Further, we recommend that organizations actively support employees' transition into remote work in terms of equipment and offer advice on reducing remote work stress, such as taking breaks or preventing isolation. These recommendations could also include advice on building self-discipline and increasing resilience. Last, we recommend organizations consider using ICTs to motivate employees when working from home. Since it is impossible to order Pizza or buy a Coke for everyone in the office kitchen when employees work remotely, organizations need to consider other ways to treat their employees. Ideas include (1) using digital nudging to remind employees to engage with team colleagues, (2) an organization-wide charity run (or walk), where employees can collect miles as a team, (3) vouchers for video on demand or audiobook platforms to help employees occupy their children and (4) the delivery of fruit and vegetable boxes.

4.2 Limitations and Future Research

Our studies are limited in terms of the sample. We only gathered data from one cultural context that did not support working-from-home opportunities before the pandemic. For example, this could influence the perception of organizational support, as the sudden change to remote work has hit many organizations unprepared. Also, we identify immediate and long-term consequences of remote stress in Study 1, which we validate with a survey that captures only one point in time. However, our sample consists of remote workers who have spent at least nine months working remotely and can assess both types of consequences. The combination with our interview study compensates for the weakness in the explanatory power here because we can retrieve causality from our interviews (Venkatesh et al. 2013). Further, we focused on remote work stress steaming from work stress and the physical separation from the conventional workspace, leaving technology-driven stressors aside. Nevertheless, we encourage future research to understand remote work stress as a socio-technological phenomenon and capture its aspects. Also, recent research acknowledges the role of personal characteristics in dealing with stress (e.g., Pflügner et al. 2021), which could add a valuable perspective to remote work stress. For example, literature has identified self-discipline to help establish routines and stay focused on work tasks (Soto et al. 2011), which could also help deal with the experienced changes due to remote work and positively affect the perceptions of remote work stress. Further, we want future research to take an expansion approach (Venkatesh et al. 2013) and investigate the insignificance of the influence of fear of rejection. The current results indicate that fear of rejection can positively or negatively influence perceived job performance, which requires a deeper understanding of whether additional factors contribute to the actual effect of fear of rejection. Those investigations would help categorize the impact of employees' stress perception and mental health.

5 CONCLUSION

Organizations have to face the difficult decision of whether to offer their employees working-from-home opportunities that, on the one hand, are desired by a majority of employees (Oliveros 2021) and, on the other hand, burden employees' mental health (Robinson 2021). We contribute to this discussion by applying a mixed-methods approach that offers a remote work stress model, outlining remote work stressors and adverse consequences for employees. We show that remote work stress is a socio-technological stress phenomenon that requires addressing specific remote work characteristics. Further, we show that remote work stress can reduce organizational commitment, putting organizations at risk of losing employees. We recommend managing remote work stress early by offering best practices for communication, supporting employees' transition into remote work, and helping them better cope with it.

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APPENDIX A: INTERVIEW GUIDELINE

Interview Guideline	
General Home Office and COVID-19 Questions	How has your experience been with working from home during the COVID-19 pandemic so far? How has your daily work routine changed while working from home compared to an office on-site? Was there anything you found particularly challenging about the transition to remote work?
Social Work Environment	How does working from home influence communication and collaboration with your team members and supervisors? How have you experienced sharing and receiving feedback with or from colleagues and supervisors? Imagine a team member who may struggle with the transition to remote work. What options does your organization offer to support such an employee?
Working Conditions	Imagine an average employee's workday at home: How do you think working from home influences their regular working hours and private life? How do you perceive your work situation at home regarding the adequacy of your technical equipment?
COVID-19	In your opinion, how does the COVID-19 pandemic influence an average employee's usual level of productivity at work?

Table 4. Semi-Structured Interview Guideline

APPENDIX B: CODING EXAMPLE

Example Code	Descriptive code	Interpretative Code	Category
"There, you knew each other quite well from the office, so you could gauge people more easily and knew, for example, from their tone of voice, how they were feeling at that moment." "As there is no sound, much communication gets lost. This is one of the greatest difficulties or challenges I recognized for myself, particularly because I did not know my superior and her way of communicating."	Lack of work environment understanding; lack of body language, intonation, and facial expressions; prior knowledge	Reduced communication quality	Remote work stressor
"You are left wondering about your performance, which can make you more unsatisfied with your own work than you should be because you are missing the approval or feedback." "You are always interested in doing what you do well and get better, and when you receive a task, you want to complete it well. If you do not get any feedback at all or rarely and do not know if it was good or bad, you become insecure and less content."	Lack of appreciation; lack of contact; lack of feedback; inefficient collaboration; work-life-balance; job-opportunities	Job satisfaction	Immediate remote work consequence

Table 5. Coding Example

APPENDIX C: CONSTRUCTS, ITEMS, AND LOADINGS

Measure	Items	Loadings
Role conflict (RC) adapted from Tarafdar et al. (2007)	RC01: When I work remotely, I have to do things that should be done differently.	0.776
	RC02: When I work remotely, I work under a lack of policies and guidelines.	0.768
	RC03: When I work remotely, I have to oppose a rule or policy to carry out all of my assignments on time	0.734
	RC04: I have to work under vague directions or orders when working remotely.	n.s.
Reduced communication quality (CQ) adapted from Lowry et al. (2009)	CQ01: It is hard to communicate openly with co-workers through digital technologies when working remotely.	0.707
	CQ02: Communication with co-workers is not very open when communicating through digital technologies.	0.837
	CQ03: When people communicate with each other through digital technologies, there is a significant lack of understanding.	0.837
	CQ04: When communicating through digital technologies, asking for advice from any organization member is hard.	0.780
	CQ05: When communicating through digital technologies, we must adapt our communication style to communicate effectively.	n.s.
Lack of appreciation (LA) adapted from Tourangeau and McGilton (2004)	LA01: When I work remotely, I do not feel valued for my work.	0.776
	LA02: When I or others make decisions remotely, they are rejected.	n.s.
	LA03: I have no opportunities for personal development when I work remotely.	0.909
	LA04: When I work remotely, I have no opportunities for professional development.	0.914
	LA05: When I work remotely, I do not have the flexibility to change how I organize my work.	n.s.
Lack of perceived organizational support (LOS) adapted from Farth et al. (2007)	LOS01: My organization does not care about my well-being while working remotely.	0.820
	LOS02: Help is denied or unavailable from my organization when I have a problem while working remotely.	0.851
	LOS03: I do not know where to turn to in my organization when I have a problem while working remotely.	0.817
	LOS04: My organization does not provide all the necessary equipment to ensure a functional and healthy workplace while working remotely.	n.s.
Lack of contact with supervisor and co-workers (LC) adapted from Rosen et al. (2006)	LC01: My supervisor is too busy to give me feedback when I work remotely.	0.832
	LC02: I have little contact with my supervisor when I work remotely.	0.842
	LC03: When I work remotely, I rarely interact with my supervisor.	n.s.
	LC04: When I work remotely, my co-workers are too busy to give me feedback.	n.s.
	LC05: I have little contact with my co-workers when I work remotely.	n.s.
	LC06: When I work remotely, I rarely interact with my co-workers.	n.s.
	LC07: When I work remotely, I feel there is a lack of transparency regarding my performance.	0.789
	LC08: Working remotely makes me feel isolated.	0.767
Role overload (RO) adapted from Tarafdar et al. (2007)	RO01: Since working remotely, I often have to do more work than I can handle.	0.844
	RO 02: Since I am working remotely, I am usually required to do complex tasks.	n.s.
	RO03: Since working remotely, I often work beyond actual or official working hours.	n.s.
	RO04: Since working remotely, I often attend to many problems or assignments simultaneously.	0.825
	RO05: Since working remotely, I never have enough time to do my work.	0.907
Fear of rejection (FR)	FR01: Since working remotely, I feel like my co-workers have rejected me.	0.891
	FR02: Since working remotely, I feel like my co-workers think I have a number of significant flaws.	0.884

adapted from Lemay and Clark (2008)	FR03: Since working remotely, I feel like my co-workers dislike me.	0.912
Job satisfaction (JS) adapted from Ragu-Nathan et al. (2008)	JS01: I like doing the things I do when I work remotely. JS02: I feel a sense of pride in doing my job. JS 03: My job is enjoyable while working from home.	0.930 0.906 0.889
Work exhaustion (WE) adapted from Moore (2000)	WE01: I feel emotionally drained from my remote work. WE02: I feel used up at the end of the workday. WE03: I feel fatigued when I get up in the morning and face another day working from home. WE04: I feel burned out from my remote work. WE05: Working all day remotely is really a strain for me.	0.858 0.817 0.892 0.903 0.859
Organizational commitment (OC) adapted from Bozeman and Perrewé (2001)	OC01: I talk up this organization to my friends as a great organization to work for. OC02: I feel very much loyalty to this organization. OC03: My values and the organization's values are very similar. OC04: When working remotely, I still do not want to be working for a different organization, even if the type of work is similar. OC05: It would take a huge change in my present circumstances to cause me to leave this organization. OC06: I find it easy to agree with this organization's policies on important matters relating to its employees working remotely.	0.777 n.s. 0.733 n.s. 0.753 0.719
Perceived job performance (JP) adapted from Tarafdar et al. (2010)	JP01: Working from home helps to improve the quality of my work. JP02: Working from home helps to improve my productivity. JP03: Working from home helps me accomplish more work than possible otherwise. JP 04: Working from home helps me to perform my job better.	0.858 0.896 0.831 0.910

Table 6. Constructs, Items, and Loadings

Paper V

Unintended Consequences of Technostress Mitigation:

An Employee Perspective on the Effectiveness of Mitigation Measures

Lea Reis
University of Bamberg

Christian Maier
University of Bamberg

Katharina Pflügner
University of Bamberg

Tim Weitzel
University of Bamberg

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Chapter 2: IS Use in Healthcare

Paper VI

Chatbots in Healthcare:

Status Quo, Application Scenarios for Physicians and Patients and Future Directions

Lea Reis
University of Bamberg

Christian Maier
University of Bamberg

Tim Weitzel
University of Bamberg

Reis, Lea; Maier, Christian and Weitzel, Tim (2020): Chatbots in Healthcare:
Status Quo, Application Scenarios for Physicians and Patients and Future Directions, *In: Proceedings of the 28th European Conference on Information Systems (ECIS)*
https://aisel.aisnet.org/ecis2020_rp/163

Paper VII

Explaining Resistance to Using Chatbots in Healthcare:

An Illustration of How to Include Configurational Approaches in Contextualized IS Research

Lea Reis
University of Bamberg

Christian Maier
LMU Munich School of Management, Ludwig-Maximilians-Universität München

Jens Mattke
University of Bamberg

Tim Weitzel
University of Bamberg

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Explaining Resistance to Using Chatbots in Healthcare: An Illustration of How to Include Configurational Approaches in Contextualized IS Research

ABSTRACT

Most patients are aware of the benefits of AI integration into anamnesis. Still, they resist using an AI-based chatbot for collecting medical data and prefer to stick with the status quo without AI. Using the status quo bias perspective that provides us with factors that jointly cause resistance evolving from uncertainty about potential consequences, we follow the guidelines of Hong et al.'s (2014) context-specific theorizing to develop a contextualized model. While context-specific theorizing has focused on separate effects of variables, we want to put the interactions among the variables at the center of our analysis to understand how the presented factors jointly lead to patient resistance. To this end, we integrate configurational approaches to examine the interplay of variables within and outside the contextualized model. The potential of these methods lies in disclosing the role of certain variables in combination with others. This allows analyzing for asymmetric influences specifying such roles and helps to rate variables regarding their importance for jointly yielding a certain outcome. Applying this approach to resistance toward AI-based chatbots, we identify four configurations that jointly lead to high patient resistance and one that yields low patient resistance. Compared to traditional analyses, for example, the role of loss aversion completely changes within the configurations when combined with distrust and dispositional resistance to change. The findings contribute to context-specific theorizing in IS research by integrating configurational approaches that focus on both the contextualization of variables and the contextualization of the interplay to research treating status quo bias perspective by clarifying how and why the presented variables in the theory jointly lead to resistance, and to research on resistance to AI-based chatbots in healthcare, by explaining the gap between attested benefits and actual resistance to AI-based chatbots of patients.

1 INTRODUCTION

When consulting a physician, patients must answer numerous questions about their condition, symptoms, and medical history. This so-called anamnesis (Grüne 2016) is important, as the quality and safety of diagnostics and treatments are significantly affected by the accuracy and completeness of the patients' recorded medical data (Kassirer 2014). In the same vein, collecting the patients' medical data is time-consuming and not billable. So, there are several attempts to reorganize the data collection with the help of information systems (IS) (Vogel et al. 2016). The most promising way to realize 'self-service' opportunities for collecting data is by using AI-based chatbots. AI-based chatbots are communication interfaces of cognitive agents that use natural language processing and machine learning to communicate with users (Davenport and Ronanki 2018). These communication skills enable patients to answer systematic questions about their health condition without the direct involvement of a physician (Denecke et al. 2018). According to recent reports (Deloitte 2019), most patients agree that integrating an AI-based chatbot into anamnesis provides quicker and easier access to healthcare, enables faster diagnoses, and improves treatment through better data availability and analysis. At the same time, though, 61 percent of patients do not want to engage with an AI-based chatbot for collecting medical data due to the uncertainty about the potentially negative consequences, such as misdiagnoses, that might come with the AI integration (PricewaterhouseCoopers 2020). So, although patients see the benefits of using AI-based chatbots, they still prefer to stick with their status quo of providing medical data.

IS research defines such negative behavioral user responses towards a new IS or the related change as behavioral resistance (Kim and Kankanhalli 2009), resulting from a subjective process where the user assesses characteristics of an IS as negative (Laumer et al. 2016). To explain behavioral resistance resulting from preferring to stick to the status quo over changing to an uncertain alternative state with uncertain consequences (here: using the AI-based chatbot), which we further refer to as resistance, IS research has built on the status quo bias perspective (SQBP) (Samuelson and Zeckhauser 1988). The SQBP provides a set of variables that, in combination, jointly lead to a bias in favor of the status quo and, hence, explain resistance. When using SQBP to explain the resistance to a specific IS, IS research has typically contextualized the theory, e.g., by adapting the general theory to the specific use context such as mobile payment systems or enterprise IS (Gong et al. 2020; Kim and Kankanhalli 2009; Lee and Joshi 2017; Polites and Karahanna 2012). The benefits of contextualized theorizing lie in the possibility to adapt general theories, such as the SQBP, to a specific use context, which makes the deduced models and results more accurate and robust and increases their applicability for practice (Bamberger 2008; Hong et al. 2014). For doing so, IS research suggests, first, contextualizing the *variables* of the general theory, which enables a better adaptation to the set of factors surrounding an examined phenomenon (here: resistance to IS), such as specific characteristics of the IS, the user, and the use context. Second, IS research suggests also examining the contextualized *interplay* between those variables (Hong et al. 2014), based on the tenet that when considered together in sets, the interplay of variables can yield a more interpretable and theoretically interesting pattern than any of the variables would show in isolated examination (Johns 2006). So far, contextualized IS research has primarily focused on contextualizing variables (see Appendix A for a review). This leaves room for studying the contextualized interplay of variables, which will provide additional insights into their multidimensional interactions, i.e., the role and importance of variables in causing a phenomenon in combination with others. Focusing on the variables of SQBP and also the interplay among them, we will use the guidelines of context-specific theorizing (Hong et al. 2014) and explain which of the variables in combination as a set lead to resistance and how they interact within the context of using AI-based chatbots for collecting medical data. To this end, the latest research in the field of IS suggests configurational methods to be especially suited to examine multidimensional interaction of variables, as they uncover the role of certain variables in combination with others, offer the possibility to analyze for asymmetric influences specifying that role and help to rate variables in their importance for jointly yielding a certain outcome, (Benlian et al. 2018; Pappas and Woodside 2021; Park et al. 2020).

Against this backdrop, this study aims to illustrate **how we can use configurational methods within the guidelines of context-specific theorizing to contextualize the SQBP to eventually explain patients' resistance to using an AI-based chatbot for collecting medical data in healthcare**. To fulfill our purpose, we first present existing knowledge on resistance to AI-based chatbots in healthcare, the SQBP (Samuelson and Zeckhauser 1988), and context-specific theorizing in IS research (Hong et al. 2014). Then, we illustrate how we apply and enrich the existing guidelines with configurational approaches, here qualitative comparative analysis (QCA), using the example of patients' resistance to AI-based chatbots for collecting medical data. Last, we elaborate and discuss how applying QCA can advance the understanding of the interplay of variables within context-specific theorizing in IS research.

2 THEORETICAL BACKGROUND

Laying the base to contextualize SQBP in the context of patients' resistance to using an AI-based chatbot for medical data collection during anamnesis, we first provide insights from our context, presenting existent research on resistance to AI-based chatbots in healthcare and the SQBP. Then, we elaborate on the existing knowledge and guidelines on context-specific theorizing in IS research.

2.1 User Resistance to AI-based Chatbots in Healthcare

AI-based chatbots, defined as communication interfaces of cognitive agents that use natural language processing and machine learning to communicate with users (Davenport and Ronanki 2018), offer a promising opportunity to increase the accuracy and quality of stored medical data through direct communication with the patient without any involvement of a physician (McKinsey 2020). The AI-based chatbot collects and provides a structured digital recording of the medical data stored in an electronic health record (EHR), which is sharable among physicians and avoids data duplication (Denecke et al. 2018). In the field of medical data collection, recent research highlights the use case of collecting medical data with the help of AI-based chatbots during anamnesis (Denecke et al. 2018), referring to the part of consultation where the physician asks questions about the patient's medical history, family, nutrition, medication, and habits (Kassirer 2014). To realize the described benefits, patients need to be willing to share their data with it, which a major portion is not (PricewaterhouseCoopers 2020). Instead of providing the AI-based chatbot with their medical data, patients prefer to stick with their current form of consultation and resist using the AI-based chatbot (see Figure 1).

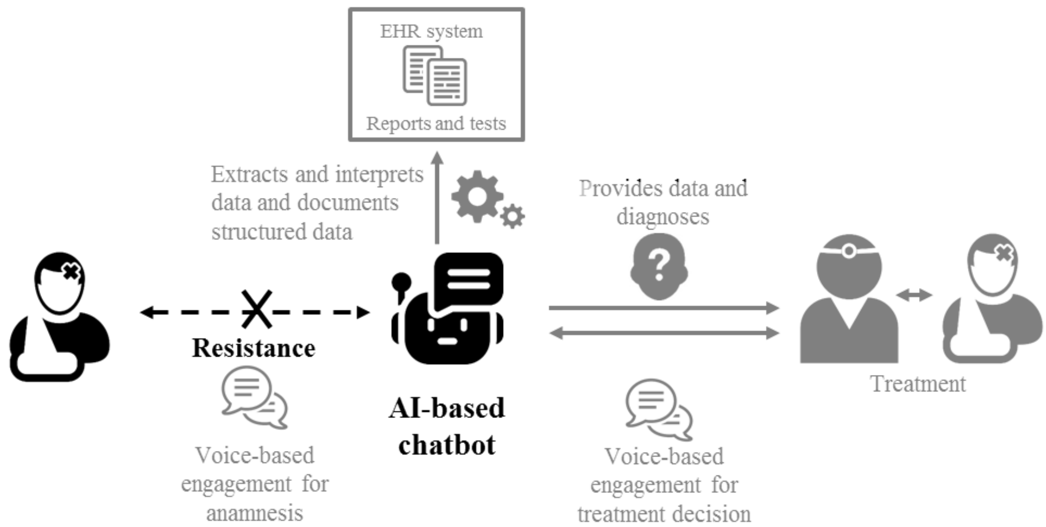

Figure 1. The Focus of this Study

Prior research on AI-based chatbots in healthcare has only considered positive user reactions to the described use case (Denecke et al. 2018), leaving the observed patient resistance untouched (PricewaterhouseCoopers 2020). While lots of research in the stream of resistance to IS in healthcare has tackled the topic of resistance (see Table 3 for a review) and offers valuable insights, the results do not respect the specific context of using AI-based chatbots for medical data collection during anamnesis. Among others, the communication abilities of AI-based chatbots differ from more “traditional” IS in healthcare and may raise specific worries regarding direct interaction with the patient, which needs to be considered when studying resistance (Reis et al. 2020). Further, those studies foremost consider the physicians’ perspective. Patients, however, represent the demand side of healthcare with motivations, aims, and perceptions different from the supply side (Penman et al. 1984). Therefore, examining the reasons for patients’ resistance to AI-based chatbots for medical data collection during anamnesis remains understudied so far and needs further investigation that includes the observed resistance resulting from the uncertainty about the potentially negative consequences that might come with the AI integration (PricewaterhouseCoopers 2020).

2.2 Status Quo Bias Perspective

The SQBP rests on the assumption that individual decision-making is biased in favor of the status quo (Samuelson and Zeckhauser 1988). This means that their decision to resist changing the status quo for an uncertain state is not only grounded in rational decision-making in the form of a (1) cost-benefit analysis but influenced by biases in the form of (2) cognitive and (3) psychological factors that bound the rationality in decision-making (Lee and Joshi 2017). Against this backdrop, to explain resistance, SQBP provides six variables that fall into those three main categories that jointly cause a status quo bias (Samuelson and Zeckhauser 1988).

First, *rational decision-making* can explain status quo bias, when rationality requires deciding in favor of the status quo in a cost-benefit analysis. Transition and uncertainty costs are influencing factors contributing to this cost-benefit analysis (Lee and Joshi 2017). *Transition costs* make every switch from the status quo costly and contribute to status quo bias if the costs for switching exceed the efficiency gain associated with change (Samuelson and Zeckhauser 1988). *Uncertainty costs* involve investing time and resources to assess the alternatives to the status quo under uncertainty, including the consequences. The chance of failure with the status quo is low, contributing to the status quo bias. Second, status quo bias appears when *cognitive misperception* biases the assessment of the alternative state in favor of the status quo. *Loss aversion* is an influencing factor contributing to this cognitive misperception, as potential losses associated with the status quo weigh larger than potential gains, influencing the assessment in favor of the status quo (Samuelson and Zeckhauser 1988). Third, status quo bias can be explained by *psychological commitment* towards the status quo, as individuals tend to justify their actual situations in subsequent decisions to confirm the correctness of their decision-making and to keep control. Influencing factors contributing to this commitment are sunk costs, anticipated regret, and decisional control (Samuelson and Zeckhauser 1988). *Sunk costs* refer to investing time and resources to reach the status quo. The greater the investment, the stronger individuals need to retain the status quo. *Anticipated regret* describes individuals trying to avoid threats or consequences, enabling the future feeling of having made a wrong decision (Liang and Xue 2009). Maintaining the status quo can also result from efforts to assume *decisional control*. Actively deciding in favor of the status quo gives the illusion of better control (Samuelson and Zeckhauser 1988).

While the SQBP provides us with the insights that those factors jointly result in a bias for the status quo and eventually lead to an unwillingness to change to an uncertain situation, the measurement of those joint effects has not been part of the original work (Samuelson and Zeckhauser 1988). Existing studies contextualizing SQBP to explain the unwillingness to change to a new IS, so resistance, in IS research (e.g., Gong et al. 2020; Kim and Kankanhalli 2009; Polites and Karahanna 2012) decided to analyze the separate effects of the provided variables by using structural equitation modeling. While this offers valuable insights into how the variables of the SQBP influence resistance individually, the original assumption that the factors provided by the SQBP have a certain interplay that jointly results in a status quo bias that leads to resistance is underrepresented. However, this assumption of the SQBP is also supported by the latest research on change behavior, stating that whether an individual supports or resists change cannot be explained with the analysis of separate factors but results from a potentially complex interplay among factors that in combination jointly lead to support or resistance (Oreg et al. 2011; Straatmann et al. 2018). Further, we aim to contextualize the SQBP to explain resistance to AI-based chatbots for collecting medical data and existing guidelines in context-specific theorizing (Hong et al. 2014) advice to examine possible interactions among variables explicitly. To elaborate on these interactions best, we follow recommendations in IS research (Benlian et al. 2018; Pappas and Woodside 2021; Park et al. 2020) and include configurational methods in our contextualization.

2.3 Context-Specific Theorizing in IS Research

Numerous studies in recent information systems (IS) and management research have stressed the necessity of context-specific theorizing (Burton-Jones and Volkoff 2017; Maier et al. 2021b) to shape the influence of context on our research outcomes. The term context has evolved from early research considering context as potential situational and temporal boundary conditions to theories to nowadays' research considering it as *the set of factors surrounding a phenomenon* that drive cognition, attitudes, and behavior (Bamberger 2008; Whetten 2009). To incorporate context into theories, research suggests single-context theory contextualization.

Contextualization thereby describes the process of reaching context-specific theorizing through adapting a general theory to a specific context. This allows considering a certain set of factors surrounding the phenomenon at hand to influence the studied cognition, attitude, and behavior (Hong et al. 2014). To perform context-specific theorizing through contextualization, prior research came up with specific guidelines (Hong et al. 2014). The guidelines suggest advancing in three stages, each encompassing two steps (see Table 1). The first stage addresses the selection (Step 1) and refinement (Step 2) of a general theory and aims at the contextualization of already existing variables in the model, for example, by replacing the general dependent variable with a context-sensitive one. Context sensitivity expresses the same concept across contexts with minimal adaptations (Whetten 2009). In the context at hand, we would replace the dependent variable “resistance” with the context-sensitive variable “resistance to AI-based chatbots” while the core definition of resistance survives. The second stage treats the identification (Step 3) and integration (Step 4) of context-specific variables into the refined general theory to get a contextualized model, for example, by adding context-specific variables. Context specificity refers to certain factors existing only within a certain context (Whetten 2009), such as additional variables or geographical or cultural aspects (Venkatesh et al. 2010). The third stage addresses the interplay among the variables in the contextualized model and their interplay with context-shaping factors outside the actual model and the interplay among them (Step 5 and 6), for example, with factors related to the respective IS, its users, and the use context (Hevner et al. 2004). Those factors are causally related to the studied phenomenon, and their interplay has been examined so far by identifying alternative models based on the contextualized model that integrates anteceding or moderating effects between variables.

As stressed by the guidelines (Hong et al. 2014), one tenet of prior studies conceptualizing contextualized theorizing in IS research is that a better understanding of the interactions, so the interplay of variables considered together in sets, can yield a more interpretable and theoretically interesting pattern than any of the variables would show in isolation (Johns 2006). Existing studies using those guidelines rely on separate effects from anteceding, mediating, or moderating relationships to examine interactions. While these insights are valuable, they rather characterize the separate relation of each variable in influencing the outcome, not the interactions between them, meaning the interplay among variables and between variables and context-shaping factors outside the contextualized model (see Appendix A for a review). In contrast to that and respecting the idea of the guidelines, the SQBP that we aim to contextualize with these guidelines assumes that not the separate effects of the contained variables but the multidimensional interaction among them as a set jointly lead to status quo bias and eventually drive resistance (Samuelson and Zeckhauser 1988). However, measuring those joint effects has not been part of the original work, neither for the SQBP nor the guidelines of context-specific research. To examine those multidimensional interactions, the latest IS research sees benefits in configurational approaches providing insights into the role and importance of variables within the interplay with others (Benlian et al. 2018; Pappas and Woodside 2021; Park et al. 2020). While configurational approaches have not been included in prior guidelines on context-specific theorizing, we want to take the opportunity and suggest leveraging the benefits of using configurational methods in this field. A detailed illustration of how to use configurational methods in context-specific theorizing is provided next, using the example of contextualizing SQBP to explain resistance to AI-based chatbots for collecting medical data.

Stage	Step	Description
Respecting context-sensitivity	*Step 1: Ground in a general theory*	Select a general theory relevant to the context and linked to the research objectives. The theory can be established or emerging and contextualized to an established or emerging context.
	Step 2: Contextualizing and refining the general theory	For example, bring the theory to a specific context by replacing the general dependent variable with a context-sensitive one and refining the model to include the minimal set of existing variables for the context.
Adding context-specificity	*Step 3: Thorough evaluation of the context to identify context-specific Variables*	Identify context-specific variables that you add to the model as additional variables through either literature, observation, or interviews.
	Step 4: Modelling context-specific variables	Include the context-specific variables into the model, either by decomposing the variables into context-specific variables or by adding context-specific new variables having a direct or indirect influence on the dependent variable.
Examining interactions	*Step 5: Examination of the interplay of the IT artifact and other factors*	Examine the context-shaping factors outside the contextualized model addressing the specific IS, the user, and the use context and their interplay with the contextualized model through direct or indirect effects.
	Step 6: Examination of alternative context-specific models and the interplay among variables	Identify alternative models based on the contextualized model that integrates anteceding, mediating, or moderating effects between variables, such that there are equifinal solutions to the context-specific theorizing.

Table 1. Guidelines for Context-Specific Theorizing in IS Research (adapted from Hong et al. (2014))

3 ILLUSTRATING THE USE OF CONFIGURATIONAL METHODS IN CONTEXT-SPECIFIC THEORIZING

3.1 Contextualization of Variables: Coming Up with a Contextualized Model

In line with existing guidelines (Hong et al. 2014) presented in Table 1, we select a general theory that fits the phenomenon we want to explain (Step 1). Examining resistance resulting from uncertainty, the SQBP fits the interests of the selected context, as it is based on the tenet that individuals' decision-making is biased in favor of the status quo when individuals resist changing the status quo for an uncertain alternative state (Samuelson and Zeckhauser 1988). Taking SQBP as a base, in the first stage, we decide that each of the variables provided in the SQBP is relevant to our context, as prior research argues that to examine status quo bias, we need to consider the SQBP as a whole instead of selecting specific subsets of variables (Lee and Joshi 2017). Therefore, we keep the existing variables as a minimum subset to explain patients' resistance and adapt them to be more context-sensitive (Step 2) by defining them in the context of using AI-based chatbots for collecting medical data and by adjusting the related measures to this specific use context. To that end, we define the variables of the SQBP in the context of patients' resistance to AI-based chatbots (see Table 2) and refine them on the item level with context-sensitive items (for detailed information on the measures, please see Appendix B).

Category from SQBP	Context-sensitive variable	Adapted definition in the context of patients' resistance to AI-based chatbots
Resistance	Patients' resistance to AI-based chatbots	Negative behavioral response toward an AI-based chatbot used for medical data collection
Rational decision making	Transaction costs	Patients' assessment of the time and effort required to adapt to using an AI-based chatbot for collecting medical data.
	Uncertainty costs	Patients' assessment of information search and analysis efforts for patients' decision-making on whether to use AI-based chatbots for collecting medical data.
Cognitive misperception	Loss aversion	Patients' tendency to weigh the costs of using an AI-based chatbot for collecting medical data is larger than the benefits.
Psychological commitment	Sunk costs	Patients' assessment of the effort and time invested in establishing and following the current consultation form.
	Anticipated regret	Patients' assessment that they will regret to use an AI-based chatbot for collecting medical data.
	Decisional control	Patients' perception is that they control the situation and can freely decide whether to use the AI-based chatbot or not.

Table 2. Enriching the SQBP with Context-Sensitivity

Since SQBP provides us with the insights that the presented variables in combination jointly result in a bias for the status quo and eventually lead to an unwillingness to change to an uncertain situation (Samuelson and Zeckhauser 1988), we assume that this also applies to the context-sensitive variables of our so far contextualized model (see Table 2). Therefore, we conclude that the context-sensitive variables together as an interrelated set jointly lead to patients' resistance to using AI-based chatbots for collecting medical data. Including this in our so far contextualized model, we get the following (see Figure 2):

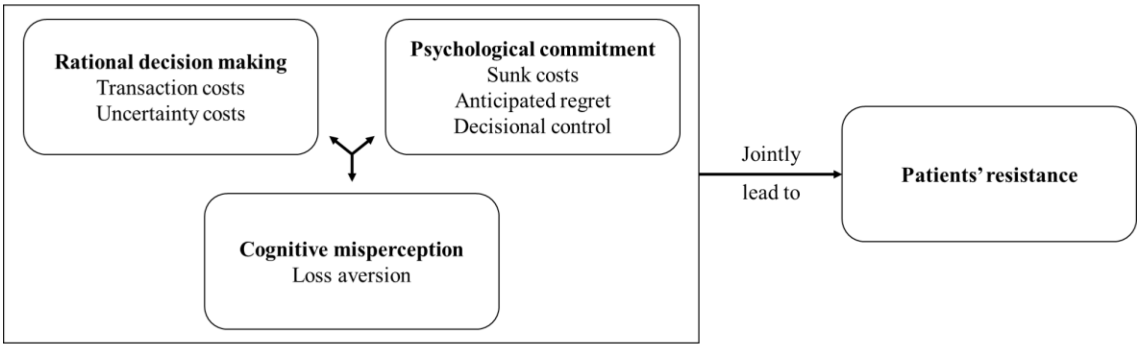

Figure 2. Model Including Context-Sensitive Variables

To further contextualize this model to patients' resistance to using AI-based chatbots for collecting medical data, in the next stage, we will also respect the influence of factors that are important in this context but are not yet captured by the context-sensitive model based on SQBP (Step 3). To identify those context-specific variables that contribute to patients' resistance, we follow recommendations (Hong et al. 2014) and consult existing literature on resistance to IS in healthcare (see Table 3) since resistance to AI-based chatbots in healthcare has not yet been touched explicitly by prior IS research.

Paper	**IS**	**Perspective**	**Context-specific variables**
Bhattacherjee and Hikmet (2007)	EHR system	Physicians	Distrust
Doolin (2004)	EHR system	Physicians	Distrust
Hsieh (2015)	Health cloud	Healthcare providers	Regret avoidance
Kane and Labianca (2011)	EHR system	Healthcare-Groups	Distrust
Mettler et al. (2017)	Service robots	Physicians and medical personnel	Distrust
Murungi et al. (2019)	EHR system	Physicians and medical personnel	Distrust
Nov and Schecter (2012)	EHR system	Physicians	Dispositional resistance to change, distrust

Table 3. Context-Specific Variables from Existing Research Treating IS Resistance in Healthcare

Those studies reveal physicians' distrust in the IS as a major influencing factor in IS resistance in healthcare (e.g., Bhattacherjee and Hikmet 2007; Mettler et al. 2017), as medical data is very sensitive (Kassirer 2014) and physicians need to rely on the data provided by the IS for diagnosis and treatment (Pinsonneault et al. 2017; Prince et al. 2018). Furthermore, prior literature identifies the dispositional resistance to change as an influencing factor that excludes long-term resistance prevention due to the propensity to resist (Nov and Schecter 2012). Based on the identified factors from prior literature, we define two context-specific variables to be added to our so-far-contextualized model (Step 4): distrust and dispositional resistance to change (see Figure 3). Adapted from prior research conceptualizing trust (Mcknight et al. 2017), we define *distrust* in the specific context of patients' resistance to using AI-based chatbots for collecting medical data as the assessment that an agent, here the AI-based chatbot is deceitful, malevolent, and incompetent, which biases the rational evaluation of risks and benefits associated with the change. Further, adapted from prior research (Oreg 2003) to the context of patients' resistance to using AI-based chatbots, we define *dispositional resistance to change* as an individual's propensity to decide in favor of resisting the change in conducting medical data collection because of a short-term focus on benefits, cognitive rigidity, routine seeking, and negative emotional reactions. Integrating those context-specific variables results in the following contextualized model (see Figure 3):

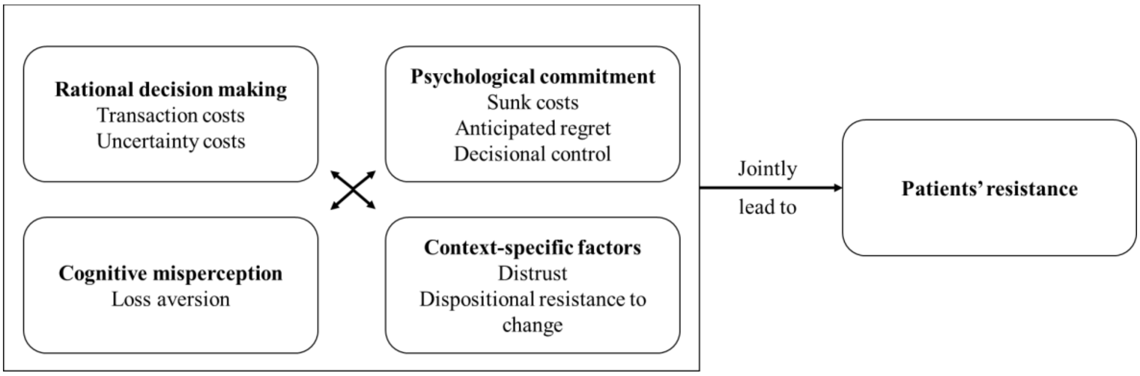

Figure 3. Contextualized Model Including Context-Sensitive and Context-Specific Variables

With our contextualized model, we will explain patients' resistance to using AI-based chatbots resulting from sets of context-sensitive and context-specific variables. In line with existing guidelines (Hong et al. 2014) and SQBP (Samuelson and Zeckhauser 1988), this involves the analysis of the variables that, in combination with other variables, jointly lead to patient resistance and the interactions, so the interplay among variables and with context-shaping factors outside the actual contextualized model (Step 5). To this end, we follow recommendations in the latest IS research (Benlian et al. 2018; Pappas and Woodside 2021; Park et al. 2020) to analyze interactions with configurational methods and apply fuzzy-set qualitative comparative analysis (fsQCA) to our contextualized model. We outline our approach and methodology in the next section.

3.2 Contextualization of the Interplay: Analyzing the Interactions of the Contextualized Model with Configurational Methods

Following the guidelines of context-specific theorizing in IS research (Hong et al. 2014), in the third stage, we want to explain the interactions of our contextualized model so the interplay among the variables of our contextualized model and the interplay with context-shaping factors outside the actual contextualized model, to uncover the role and importance of variables in combination with others. To this end, we split our analysis into two parts, one dealing with the combinations of variables and the interplay among them jointly leading to patients' resistance to using AI-based chatbots for collecting medical data during anamnesis and one dealing with the interplay of the model with context-shaping factors outside the actual contextualized model.

Both analyses are based on the same data set and analysis approach, which we outline next, followed by the results of our two analyses and their validation.

3.2.1 Sample and Data Collection

*Ou*r sampling strategy was to attract individuals who have consulted their physician at least once within the past year, as we wanted them to be able to assess their current consultation form and treatment situation compared to the possibility of using an AI-based chatbot for collecting medical data in the future. For this, we used a screening question and asked the participants how often they had seen a physician for consultation in the past year. If the answer was zero, the participant was left out. Further, we only asked individuals who have not yet used an AI-based chatbot for medical data acquisition in anamnesis. For this, we used one screening question about the previous use of AI-based chatbots. We only allowed participants who passed the screening question (‘Have you ever used an AI-based chatbot for collecting medical data before?’). To ensure high quality in the survey and to only have participants who carefully read the instructions, we only allowed participants who successfully solved a Captcha and who successfully answered screening questions to ensure that they are paying attention (‘This question is to ensure you are not a robot application and that you pay attention to the questions. Please select 'Exit' to continue to the next questions in this study.’), which is an established approach and also recommended in the literature (Lowry et al. 2016). We prepared an online survey using Amazon Mechanical Turk (mTurk), which is a valid data collection approach equal to traditional data collection approaches (Lowry et al. 2016) and frequently applied in research to identify distinct types of individuals (Bennett et al. 2016). As we aim to reach distinct types of patients for a representative sample, we assess mTurk as a suitable form of data collection to examine resistance in healthcare.

Biological sex in percent		**Frequency of medical consultation per year in percent** (Mean: 2.93)	
Male	42.13	1	38.20
Female	57.87	2	18.54
Other	0.0	3	17.42
		4	10.11
		5	5.62
		>5	10.11
Age in percent (Mean: 34.04; SD:10.71)		**Highest education level in percent**	
18-20	6.75	High school / GED	14.04
21-30	45.51	Some college	14.61
31-40	25.28	2-year college degree	17.42
41-51	14.04	4-year college degree	34.83
51 - 60	7.30	Master’s degree	14.04
61 - 70	1.12	Professional degree	5.06

Table 4. Demographics (N=175)

We removed six invalid responses from the participants who passed all screening questions as they indicated a higher working experience than their age. Ten answered two attention tests (‘Please click on ‘strongly agree’’) wrong (Lowry et al. 2016). The final sample consists of 175 individuals. The demographics are displayed in Table 4. Since the sample represents relatively young participants with a mean age of 34.04, we examined the influence of Age in a post-hoc analysis (see Table 12 in the Appendix). For the fsQCA method, the minimum required sample size to avoid finding random sufficient configurations for this study is 45, as the ratio of cases to conditions, here eight for the first analysis and nine for the second, needs to be lower than 0.2. (Marx 2010; Marx et al. 2014). Therefore, we can say that we fulfill the sample size requirements in this study. This study relies on self-reported data, and even though the participants were unaware of the study's goal, we tested whether common method bias distorts our data. The three test results show that CMB is not an issue in this study (see Appendix C).

3.2.2 Measurement Model

To ensure *content validity,* we only used items validated in previous research (see Appendix C). All item loadings were higher than 0.707, which shows that *indicator reliability* is given (Carmines and Zeller 2008). To test for construct reliability, we tested for the average variance extracted (AVE) and composite reliability (see Appendix D). The AVE of each construct is higher than 0.50, and the CR for each construct is higher than 0.70, which shows high *construct reliability*. We can ensure discriminant validity, as the square root of the AVE is higher than the corresponding correlations of the constructs (Fornell and Larcker 1981) (see Appendix D). Furthermore, we calculated the heterotrait-monotrait (HTMT) ratio of 0.72. This is lower than the absolute $HTMT_{0.85}$ criterion (Henseler et al. 2014) and, therefore, shows that *discriminant validity* is given.

3.2.3 Methodological Approach

To analyze our data and to explain the interplay among the variables of our contextualized model and with context-shaping factors outside the actual contextualized model, we base on a set-theoretic configurational approach (El Sawy et al. 2010; Misangyi et al. 2017) and use fuzzy-set qualitative comparative analysis (fsQCA) (Ragin 2000). FsQCA is currently the dominant and most appropriate data analysis method for set-theoretic configurational approaches. It enables the analysis of sets of variables, which we further refer to as configurations and their interplay. It is increasingly prevalent across the business and behavioral sciences and gaining attraction in IS research (e.g., Bui et al. 2019; Chong et al. 2013; Dawson et al. 2016; Iannacci and Cornford 2018; Liu et al. 2017; Nishant and Ravishankar 2020; Park et al. 2020). FsQCA is an analytic method grounded in set theory and Boolean algebra that examines combinations of variables, specifically the relationship between configurations of present or absent conditions and an outcome of interest (Ragin 2014). In this study, conditions refer to the variables of our contextualized model and the context-shaping factors outside the model. Conditions and the outcome are represented as fuzzy sets to differentiate two extreme situations of set membership (Ragin 2000). A condition (e.g., distrust) can be fully in a set, represented by the fuzzy set value of 1 (e.g., presence of distrust), or can be fully out of a set, represented by a fuzzy value of 0 (e.g., absence of distrust). All values between zero and one represent a certain membership of being fully in or out of a set. For instance, a fuzzy value of 0.80 for distrust indicates that distrust is rather present, while a fuzzy value of 0.20 indicates that distrust is absent.

For the data analysis, we used the QCA R package (Duşa 2018) and the fsQCA 3.0 software (Ragin et al. 2016). In both analyses, we proceed in five steps (see Appendix E for more details). We calibrate the survey data into fuzzy sets, which we use in both analyses. Then, we analyze for sufficient configurations. In this study, a configuration refers to a specific group of conditions associated with high resistance to AI-based chatbots for medical data collection. A sufficient configuration is a configuration that exceeds a frequency threshold of three, a raw consistency threshold of 0.85, and a PRI threshold of 0.85 (Ragin 2009). This means that sufficient configurations are only those configurations that are found to consistently yield a high resistance to AI-based chatbots for medical data collection. Multiple sufficient configurations are simplified through logical minimization. Therefore, we can say that a condition in a sufficient configuration is either present (in the results indicated with ●) or absent (in the results indicated with ⊗), or a condition can also be either present or absent, which refers to a 'don't care situation' (in the results indicated with blank space). Additionally, we analyze whether the conditions are considered core conditions, i.e., the conditions are part of the parsimonious and intermediate solution. To indicate core conditions, we use large circles in the graphical representation (Schneider and Wagemann 2012). We examine whether there are necessary conditions within sufficient configurations for all configurations. This means that a condition that is necessary always exists in configurations yielding a high, respectively a low, resistance to AI-based chatbots for medical data collection. A necessary condition must exceed the consistency threshold of 0.90, a coverage threshold of 0.60, and relevance of necessity threshold of 0.60 (Ragin 2006).

Finally, we test the results for robustness and predictive validity. We assessed whether the results were stable if we used a lower anchor for being fully-in a set and for fully-out a set and whether the results were stable if we used a higher anchor for fully in and fully out of a set. In line with recent QCA literature (Pappas and Woodside 2021), we also tested for the predictive validity of the QCA results. This means that we tested our QCA model on a test dataset that has not been used for developing the QCA model. We used the same data collection approach described above and sampled 100 participants for the test dataset. We then followed previous guidelines (Pappas and Woodside 2021) and analyzed the overall consistency of the QCA model on the test dataset. We present our data analysis approach and validation in Appendix E.

3.2.4 Analysis Part 1: Using fsQCA to explain the Interplay among the Variables of the Contextualized Model

In the first part of our analysis of the interactions, we focus on the sets of variables from the contextualized model that jointly lead to patients' resistance and the interplay among them. Our fsQCA analysis reveals four sufficient configurations (see Figure 4), so four sets of context-sensitive and context-specific factors jointly lead to a high resistance to AI.

	C1	**C2**	**C3**	**C4**
Transition costs	⊗	●		●
Uncertainty costs	⬤	⬤	⬤	⬤
Loss aversion	⊗		⊗	●
Sunk costs	⬤	⬤	⬤	⊗
Anticipated regret	●	●	●	●
Decision control	●	●	●	●
Distrust		⬤	⬤	⬤
Dispositional resistance to change	●	●		⊗
Raw coverage	0.33	0.25	0.23	0.23
Unique coverage	0.15	0.03	0.01	0.01
Consistency	0.96	0.98	0.96	0.96
PRI consistency	0.90	0.95	0.87	0.95
Solution coverage	0.41			
Solution consistency	0.95			
PRI solution consistency	0.90			

Note: Black circles (●) show high motivation, and white crossed-out circles (⊗) show low motivation. Large circles indicate a core condition. Blank spaces ( ) indicate a 'Don't care situation.' In this case, the specific condition is irrelevant to the configuration and can either be high or low.

Figure 4. Interplay of Context-Sensitive and Context-Specific Variables

The results did not reveal any necessary conditions. Looking at the context-specific variables we added to the contextualized model from outside the SQBP, we see that either distrust or dispositional resistance to change is present in all the configurations and, therefore, contributes to high patient resistance. Still, neither condition is necessary in one configuration to yield a high resistance. This aligns with other studies treating resistance in IS (see Table 3).

Interestingly, C4 mirrors the other configurations concerning the role of loss aversion and sunk costs. While loss aversion is present in C4, it is absent in C1 and C3 and ‘don’t care’ in C2. This indicates that those patients rank benefits associated with the AI-based chatbot higher than potential losses, which backs up the observation in recent reports that despite the majority of patients seeing benefits, patients still resist using the chatbot (PricewaterhouseCoopers 2020). In configurations C1 and C3, the participants did not see any difficulties using the AI-based chatbot due to the absent transition cost. Insted, they saw benefits of the AI-based chatbot, but still showes high resistance due to the other context-sensitive and context-specific variables.

3.2.5 Analysis Part 2: Using fsQCA to explain the Interplay of the Contextualized Model with Context-Shaping Factors outside the Model

In the second part of our analysis, we look at the interplay of our contextualized model with other context-shaping factors outside the actual model, for example, factors related to the respective IS, its users, and the use context (Hevner et al. 2004) that are causally related to patients’ resistance to using AI-based chatbots for collecting medical data. Therefore, we looked for factors that shape either the experience of anamnesis or the perception of the AI-based chatbot being used for it. Prior literature on IS use indicates that repeatedly undergoing the same procedures can influence the perception of IS and IS use behavior either through habit (Polites and Karahanna 2012) or fatigue (Chen and Karahanna 2018; Maier et al. 2015). Analogous, we assume that repeatedly undergoing anamnesis might influence the perception of the context-sensitive and context-specific variables describing the use of an AI-based chatbot for collecting medical data during anamnesis and, eventually, through that, the reaction to that prospective change. Therefore, we include the condition ‘high frequency of medical consultations,’ representing the number of consultations per year (see Figure 5).

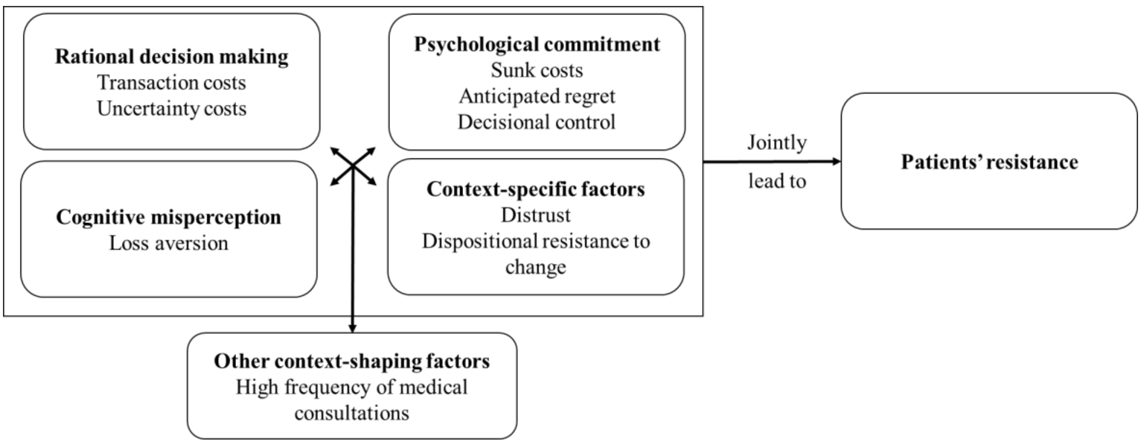

Figure 5.Contextualized Model and the Interplay with Context-Shaping Factors

To integrate the high frequency of consultations into the fsQCA analysis, we based on the fact that most people have between three and five consultations per year (Habekuß 2019). Therefore, we decided that four is the point of maximum ambiguity (fuzzy-set value 0.5), meaning that every value ≤ four will be converted into the absence of a high frequency of consultations and values above four into the presence of a high frequency of consultations. Since integrating the number of consultations per year splits our sample, we reduced the frequency threshold to three to catch the relevant sufficient configurations. To gain more insights into our QCA model, we followed QCA literature and analyzed what sufficient configurations lead to low patient resistance. This means we can also understand which context-sensitive, context-specific, and context-shaping factors jointly lead to low patient resistance. For this, we repeated the same steps for the analysis described above. We did not find sufficient configurations that lead to low resistance with the applied thresholds (consistency = 0.85, PRI consistency = 0.85, and frequency = 3). Thus, we lowered the PRI consistency to 0.75, which is still in line with recommendations from QCA literature (Lee et al. 2019; Misangyi and Acharya 2014; Park et al. 2017).

The second part of the fsQCA analysis revealed four sufficient configurations that yield a high patient resistance to AI-based chatbots for collecting medical data during anamnesis and one that yields low patient resistance (see Figure 6). Those configurations apply to either a high or low frequency of consultations. Again, we did not identify any necessary conditions. As we can see, the configurations $C1_{Ext}$, $C2_{Ext}$, $C3_{Ext}$, and $C4_{Ext}$ are the same configurations we saw in our first fsQCA analysis (see Figure 4), extended with the number of consultations per year. Whereas $C1_{Ext}$ and $C2_{Ext}$ apply to both patients with a high and low frequency of consultations, as we see a 'don't care' situation here, $C3_{Ext}$ and $C4_{Ext}$ apply to patients with a low frequency of consultations only since the condition needs to be absent in that configuration to yield high resistance. This advances the interpretability of our results, especially concerning the previously identified differences in C4. Analyzing $C4_{Ext}$, we see that sunk costs are absent, which indicates that the patients falling into that configuration are not afraid of losing their relationship with their physician, probably because they see them not too often anyway. Also, they rate the costs associated with the change higher than the benefits, indicated through present loss aversion, especially for the few occasions they need an anamnesis. Across all configurations leading to high patient resistance, anticipated regret and uncertainty costs are present, which aligns with recent reports indicating that patients' resistance to AI-based chatbots results from uncertainty about potentially negative consequences (PricewaterhouseCoopers 2020). Decision control is even present for all five configurations, indicating that the decision is free and, therefore, can be treated as a boundary condition of this case. Looking at C_{Low}, we also see that all conditions except sunk cost are absent apart from decision control. This indicates that patients showing a low resistance see the benefits of the AI integration and do not perceive any uncertainties about negative consequences. They agree that due to the AI-based chatbot, they might lose the connection to their physician. Still, as this configuration applies to a low frequency of consultations, they might not even have a relationship.

	High patient resistance				Low patient resistance
	$C1_{Ext}$	**$C2_{Ext}$**	**$C3_{Ext}$**	**$C4_{Ext}$**	**C_{Low}**
Transition costs	⊗	●		●	⊗
Uncertainty costs	⬤	⬤	⬤	⬤	⊗
Loss aversion	⊗		⊗	●	⊗
Sunk costs	⬤	⬤	⬤	⊗	●
Anticipated regret	●	●	●	●	⊗
Decision control	●	●	●	●	●
Distrust		⬤	⬤	⬤	⊗
Dispositional resistance to change	●	●		⊗	⊗
High frequency of consultations			⨂	⨂	⊗
Raw coverage	0.33	0.25	0.34	0.14	0.21
Unique coverage	0.05	0.04	0.03	0.03	0.21
Consistency	0.96	0.98	0.95	0.99	0.96
PRI consistency	0.90	0.95	0.89	0.97	0.79
Solution coverage	0.46				0.21
Solution consistency	0.95				0.96
PRI solution consistency	0.91				0.79

Note: Black circles (●) show high motivation, white crossed-out circles (⊗) show low motivation, and blank spaces ( ) indicate a 'Don't care situation.' In this case, the specific condition is irrelevant to the configuration and can either be high or low. Large circles indicate a core condition. Ext = extended high frequency of medical consultations.

Figure 6. Interplay with Context-Shaping Factors

3.2.6 Robustness validation of the results

In line with prior QCA research (Maier et al. 2021a; Park et al. 2017), we tested whether the results were stable to two calibrations (see Appendix E). For analysis 1, we find that the results are robust to changes in the calibration anchors. The solution coverage increases (0.55) when using a lower calibration anchor but decreases (0.38) when using a higher calibration anchor.

The solution consistency and the PRI consistency are well above the required threshold of 0.85 for both calibrations. Thus, we can say that analysis 1 is robust to changes in calibration. The robustness test for analysis 2 revealed the same picture. The results are stable, with slightly different consistencies and solution coverage scores. In summary, we can say that the results are resilient to changes in the calibration.

Analysis part 1	Original anchors	Lower anchors	Higher anchors
Solution coverage Solution consistency	0.47 0.95	0.55 0.96	0.38 0.92
PRI consistency	0.90	0.90	0.88
Analysis part 2	Original anchors	Lower anchors	Higher anchors
Solution coverage Solution consistency	0.46 0.95	0.55 0.97	0.37 0.93
PRI consistency	0.91	0.91	0.89

Table 5. Sensitivity analysis

In line with recent QCA literature (Pappas and Woodside 2021), we also tested for predictive validity of the QCA results. Testing the QCA model of analysis part 2 on a newly collected data sample reveals that the overall consistency of the QCA model is 0.93. The dot plot is displayed in Figure 7, where the QCA model is displayed on the x-axis, and the outcome is displayed on the y-axis. As we see in Figure 7, the lower right corner of the plot is almost empty, which underlines the high predictive consistency of 0.93. In summary, we can state that the revealed QCA model has a high predictive validity.

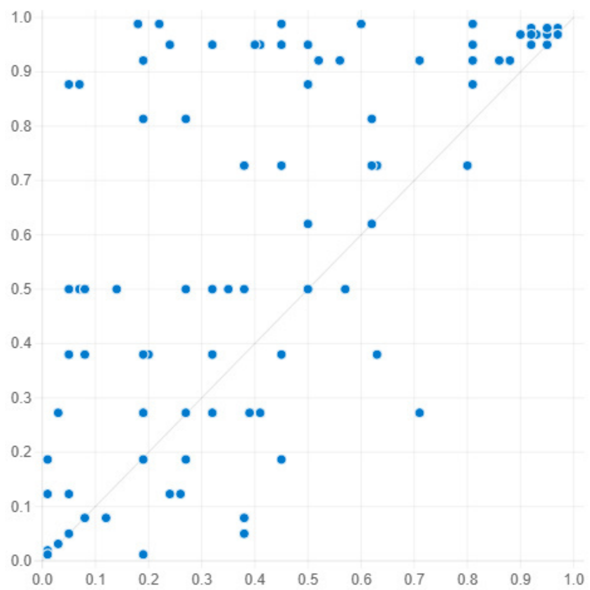

Figure 7. Dot Plot Describing Predictive Validity

4 BENEFITS OF USING CONFIGURATIONAL METHODS IN CONTEXT-SPECIFIC THEORIZING

Drawing from our results, we now want to summarize what we have learned so far and present the benefits of integrating configurational methods, such as fsQCA, into context-specific theorizing in IS research.

Using configurational approaches can yield more interpretable results. Configurational approaches allow us to yield more interpretable results by clarifying the role of variables in yielding patient resistance and the interplay among them. This also fits one primary goal of context-specific theorizing (Bamberger 2008; Burton-Jones and Volkoff 2017; Hong et al. 2014; Johns 2006; Whetten 2009) to make insights more applicable and interpretable for practice, here achieved through the combined reflection of the results across configurations. For example, in configurations C1Ext, C2 Ext and C3 Ext, patients showing a high resistance do not necessarily have a loss aversion, which we define as weighing the costs higher than the benefits. Here, the patients can see the benefits and still resist using the AI-based chatbot because they do not trust the AI-based chatbot and its capabilities or are generally unwilling to change, which clarifies the role of the context-specific variables. In $C1_{Ext,}$ even the transition costs, dealing with the difficulty of using the new technology, are absent. This means that dispositional resistance to change outweighs the perceived usefulness, attested through an absent loss aversion stressing the benefits, and ease-of-use, attested through absent transition costs, leads to high resistance. In contrast, $C4_{Ext}$ mirrors the other configurations regarding the role of loss aversion and sunk costs, with loss aversion being present and sunk costs being absent. This is surprising at first, but when we consider the context-shaping factor number of consultations, we can interpret the configuration better: patients falling into that configuration are not afraid of losing their relationship with their physician, probably because they see them not too often anyway. Also, they rate the costs associated with the change higher than the benefits, indicated through present loss aversion, especially for the few occasions they need an anamnesis. The absence analysis supports those interpretations, as the patients here are not worried about uncertain potentially harmful consequences and show low patient resistance. Those patients also admit that using an AI-based chatbot would reduce their contact with their physician. Still, as the configuration shows a low frequency of medical consultations, that does not impact the decision to use the AI-based chatbot.

Using configurational approaches can clarify the role of variables in combination with others. Using fsQCA, we concretely measure the assumed interplay of variables in the SQBP (Samuelson and Zeckhauser 1988) and show the interactions between the context-sensitive variables of the general theory react to context-specific variables and context-shaping factors. For example, the role of loss aversion completely changes within the configurations when combined with distrust and dispositional resistance to change. Only in C4 is loss aversion still present, as indicated by the general SQBP. So. in combination with context-specific variables, the contribution of loss aversion to resistance can change from the presence contributing to resistance to its absence contributing to resistance.

Using configurational approaches can reveal equifinal models explaining resistance. In general, one major benefit of configurational methods lies in the fact that they respect the equifinality of outcomes, meaning that there might be several solutions yielding the examined outcome (Misangyi et al. 2017; Pappas 2018; Pappas and Woodside 2021; Park et al. 2020). Each sufficient configuration consists of a disjunctive set of variables that equally lead to patients' resistance to AI-based chatbots. Every configuration can be seen as an instantiation of the contextualized model drawing from a specific subset of context-sensitive and context-specific variables. This enables us to accept differences in similar approaches in the existing literature to explain resistance. For example, Bhattacherjee and Hikmet (2007) explain the resistance to change mainly with perceived threats associated with the change, whereas Laumer et al. (2016) explain resistance to change from a more personality-oriented perspective as a result of individuals' dispositional resistance to change. Who is right? Our results indicate that in our context, both can be, as there is not a unique explanation but several equifinal sets of variables yielding patient resistance. Comparing $C2_{Ext}$ and $C1_{Ext}$, for example, we see that $C2_{Ext}$ is shaped by potential threats expressed through transition costs, uncertainty costs, and sunk costs, whereas $C1_{Ext}$ shows the presence of dispositional resistance to change. This indicates that both perspectives are valid, depending on the combination with other variables.

Using configurational approaches can cut down the guidelines of contextualized research to one analysis. Drawing on what we just said, the revealed configurations represent different instantiations of the contextualized model and its interactions, which is why we can cut down Step six of the guidelines (Hong et al. 2014), suggesting finding alternative models. Further, as we see, our second analysis only extends the identified configurations from the first analysis, so there is no knowledge loss between those two analyses. Therefore, we argue that after coming up with the contextualized model consisting of context-sensitive and context-specific variables and the identification of context-shaping factors outside the model that are causally related to the phenomenon of interest, **one** configurational analysis is enough to satisfy the requirements of context-specific theorizing. With our analysis, we can show 1) which of the identified context-sensitive and context-specific variables contribute to a high patient respectively low resistance, 2) the interplay among variables represented through sets of those variables jointly leading to high respectively low patients' resistance, 3) the interplay with context-shaping factors outside the model and 4) different instantiations of the contextualized model, represented through the equifinal configurations.

Taking those insights together, we see that examining the interactions with configurational approaches allows us to compare interactions throughout the contextualization and interpret results across configurations, clarifying the role of specific conditions or interdependencies among them. All in all, we, therefore, argue that our approach fits the primary goals of context-specific theorizing (Bamberger 2008; Burton-Jones and Volkoff 2017; Hong et al. 2014; Johns 2006; Whetten 2009) to make theoretical models more accurate through equifinal models explaining resistance, deduced results more robust, through configurations that are stable throughout contextualization (C2) and insights more applicable and interpretable for practice, through the combined reflection of the results across configurations.

5 DISCUSSION

Our study examines patients' resistance to using AI-based chatbots for collecting medical data resulting from the uncertainty and the unforeseen potentially negative consequences that come with AI integration. We contextualize the SQBP with fsQCA and thereby illustrate how configurational approaches can enrich context-specific theorizing in examining the specific role and importance of variables in combination with others and their interplay within the contextualized models. We identify four configurations that jointly lead to a high patient resistance and one that yields a low patient resistance, representing the interplay among context-sensitive and context-specific variables and context-shaping factors outside the model. With our findings, we contribute theoretically and methodically to context-specific theorizing in IS research, to the SQBP, and to research on resistance to AI-based chatbots. Further, we provide practical implications to address patient resistance. We present these contributions below.

5.1 Theoretical Contribution

To provide a better overview of the theoretical contributions of this study, we structure the theoretical contributions and present the contributions to context-specific theorizing in IS research first, followed by the contributions to status quo bias perspective (SQBP) and the contributions to resistance to AI-based chatbots in healthcare.

Theoretical Contribution to Context-Specific Theorizing in IS Research. This study represents an initial effort to put interactions at the center of attention for context-specific theorizing in IS research to clarify the role of variables and the interplay among them in combination with others. Although prior research develops valuable guidelines on performing context-specific theorizing in IS research (Hong et al. 2014), we see obstacles hindering IS research from leveraging the full potential of context-specific theorizing. Most papers working with those guidelines provide useful insights on the separate effects of the context-sensitive and context-specific variables of the contextualized models but miss the opportunity to examine the interplay among context-sensitive and context-specific variables and with context-shaping factors outside the model as suggested by the guidelines (see Appendix A). According to prior research, devoting less attention to the possible interplay results in an isolated examination of variables, inhibiting theoretical insights into the underlying interactions between sets of those variables (Hong et al. 2014). To address this issue, the latest research in the field of IS (Benlian et al. 2018; Pappas and Woodside 2021; Park et al. 2020) advises using non-linear, configurational methods that are especially suited to examine multidimensional interaction of those variables, as they uncover the role of certain variables in combination with others, offer the possibility to analyze for asymmetric influences specifying that role and help to rate variables in their importance for jointly yielding a certain outcome. While those configurational methods have not been included in context-specific theorizing, our illustration can advance existing guidelines in the field, which we elaborate on next. With the illustration of how to incorporate configurational methods into context-specific theorizing, we contribute to prior research with an alternative perspective that gives a clearer picture of the role and importance of variables in combination with others and the interplay among them**.**

Methodological Contribution to Context-Specific Theorizing in IS Research. Specifically, we follow invitations of prior research (Benlian et al. 2018) and propose to extend the existing guidelines (Hong et al. 2014) to advance the understanding of the interplay among context-sensitive and context-specific variables and with context-shaping factors outside the model. To this end, we suggest following the guidelines in prior research (Hong et al. 2014) to develop a contextualized model consisting of context-sensitive and context-specific variables and to identify context-shaping factors outside the model (Steps 1 to 4). Then, we suggest analyzing the contextualized model with non-linear, configurational methods to discover the role and contribution of each variable to the outcome of interest, the interplay among variables and with context-shaping factors outside the model, and different instantiations of the contextualized model, represented through the equifinal configurations (see Table 6). Our results show that context-specific theorizing needs configurational approaches to yield more interpretable results. They do so by clarifying the variables' role within the contextualized model and the interplay among them. Therefore, integrating fsQCA fulfills the initial aim of providing more robust and usable insights into a specific context (Hong et al. 2014).

Stage	Step	Description
Respecting context-sensitivity	*Step 1: Ground in a general theory*	Select a general theory relevant to the context and linked to the research objectives. The theory can be established or emerging and contextualized to an established or emerging context.
	Step 2: Identify and model context-sensitive variables	Bring the theory to a specific context by replacing the general dependent variable with a context-sensitive one and refining the model to include the minimal set of existing variables for the context.
Adding Context-specificity	*Step 3: Thorough evaluation of the context to identify context-specific variables*	Identify context-specific factors that you add as context-specific variables to the model as additional variables through either literature, observation, or interviews.
	Step 4: Modelling context-specific variables	Include the context-specific variables into the model, either by decomposing the variables into context-specific variables or by adding the context-specific factors as new variables having a direct or indirect influence on the dependent variable.
Examining Interactions	*Step 5: Identification of context-shaping factors*	Identify the context-shaping factors outside the contextualized model addressing the specific IS, the user, and the use context and their interplay with the contextualized model through direct or indirect effects. Conduct a non-linear, configurational analysis, such as fsQCA, to discover the contribution of each variable to the outcome of interest, the interplay among variables and with context-shaping factors outside the model, and different instantiations of the contextualized model, represented with the equifinal configurations.

Table 6. Updated Guidelines for Context-Specific Theorizing in IS Research

Contribution to SQBP. SQBP has been applied to examine resistance steaming from uncertainty in various IS contexts (Kim and Kankanhalli 2009; Lee and Joshi 2017; Polites and Karahanna 2012; Samuelson and Zeckhauser 1988). A commonality of these studies is that they examine the influence of individual factors separately and come to the conclusion that it is beneficial to examine the SQBP fully instead of selecting single influences, respecting all aspects of the bias and the specificities that come with them, such as the asymmetric value of loss aversion assessing risks higher than benefits (Lee and Joshi 2017). Including those insights and following established guidelines (Hong et al. 2014), we contribute to research by contextualizing SQBP in the context of resistance to AI-based chatbots for collecting medical data during anamnesis. This led to an extended SQBP that enables us to derive more interpretable and applicable insights, as intended by context-specific theorizing (Hong et al. 2014), especially through fsQCA. It delivers insights into the interactions between the identified variables that jointly lead to a bias in favor of the status quo and eventually resistance, as assumed by the SQBP (Samuelson and Zeckhauser 1988). This contributes to prior SQBP research, which is based on the analysis of individual factors separately, as we concretely measure the assumed interplay of variables in the SQBP (Samuelson and Zeckhauser 1988) and show the interactions between the context-sensitive variables of the general theory react to context-specific variables and context-shaping factors. For example, the role of loss aversion completely changes within the configurations when combined with distrust and dispositional resistance to change. Further, by using configurational methods, we better follow the assumption of the SQBP that the variables provided by the SQBP jointly, as a set, result in a status quo bias that leads to resistance (Samuelson and Zeckhauser 1988), while prior research has primarily focused on separate effects (Kim and Kankanhalli 2009; Polites and Karahanna 2012). Examining the interplay among context-sensitive and context-specific variables also shows how they contribute to resistance in combination with others. Some variables have an asymmetric relationship in contributing to resistance, meaning that their presence and absence can cause resistance equally. Also, we understand which configurations yield a low intention to resist from the same data set and present equifinal solutions yielding a high patient resistance. These insights are unique to configurational analyses and enrich the current understanding of how SQBP explains resistance. We now better understand the role of the theorized variables and see how this role and their importance change when analyzed in combination with others. This helps us better interpret the theory in terms of which factors jointly lead to resistance and why.

Contribution to Resistance to AI-Based Chatbots in Healthcare. Our paper also contributes to the specific context in which our illustration is conducted: the resistance to AI-based chatbots. Extant research has done a great job of explaining resistance in healthcare from the physicians' perspective, providing insights into why physicians resist change in healthcare, stressing the importance of distrust, for example (Bhattacherjee and Hikmet 2007; Hsieh 2015; Mettler et al. 2017). We first complement this research by providing the patients' perspective, examining the motivations and perceptions of the demand side of healthcare that differ from the supply side (Penman et al. 1984). Second, we show that resistance to AI-based chatbots for collecting medical data during anamnesis is collectively driven by equifinal subsets of variables represented by sufficient configurations. Having a closer look at those configurations, we see that loss aversion is predominantly absent, which means that the resistance to chatbots is not grounded in a lack of potential benefits of implementing the AI-based chatbot. However, anticipated regret and uncertainty costs are present in all identified configurations, yielding a high patient resistance, indicating that patients rather worry about the unforeseen negative consequences of using the AI-based chatbot for collecting medical data during anamnesis paired with distrust in the performance of the chatbot in two out of three configurations. Therefore, we show that not only physicians are responsible for the (lack of) diffusion of new IS in healthcare, but also the patients. Resistance primarily stems from the fears associated with the AI-based chatbot, not from a lack of benefits. Third, our results indicate that the resistance to AI-based chatbots for collecting medical data during anamnesis varies with the number of consultations a patient must go through annually. Remarkably, those patients showing a high frequency of configurations also show a dispositional resistance to change. This might be associated with repeatedly undergoing an anamnesis due to multiple consultations leads to a certain habit known to influence behavior in IS contexts (Polites and Karahanna 2012). In the case of $C1_{Ext}$, the dispositional resistance to change in combination with anticipated regret, uncertainty costs, and sunk costs even outweighs the seen benefits, expressed through an absence of loss aversion and the perceived easy of use of the AI-based chatbot, expressed through the absence of transition costs.

5.2 Practical Contribution

Our practical implications are twofold. First, we illustrate how configurational methods can enrich context-specific theorizing in IS research, which serves as a guideline for other researchers in the field. Based on prior research (Hong et al. 2014), the presented steps can serve as a blueprint to include fsQCA into context-specific theorizing and leverage the potentials and insights provided by a deeper examination of interactions.

Second, with the identification of sufficient configurations leading to patients' resistance to AI-based chatbots for collecting medical data during anamnesis, we provide useful insights for healthcare facilities willing to introduce such an AI-based chatbot. All configurations indicate the special importance of patients' worries that they will regret using an AI-based chatbot in the future. To overcome such anticipated regret, we suggest healthcare facilities show that there will be nothing to regret. This sounds easy but requires huge efforts regarding trust-building measures. One possibility to increase trust is to improve the explainability of what the chatbot is doing, such that the patient can better anticipate the consequences of an AI-based chatbot integration. Another possibility is to openly show how constrained the tasks of the AI-based chatbot are, identifying it as a supporting tool for physicians that enables faster and better data collection but does not compete for relevant patient time with physicians or their treatment. Looking at the configurations, we further suggest that hospitals not just focus on rational benefit spotting, as we see that resistance does not arise from a lack of benefits and address the worries and fears of the patients associated with the AI-based chatbot instead. A possible solution could be a testing version that updates prior experiences and enables a better assessment of the AI-based chatbot.

5.3 Limitations and Future Research

Limitations. This study faces some limitations regarding the selection of theory and factors. While we base on literature to identify context-specific factors treating resistance in healthcare, we acknowledge that interviews could reveal more factors to incorporate into our model, leading to different configurations. The same applies to the integration of solely one context-shaping factor. Further, we use MTurk to collect data as we strive for a more diverse population. However, this is also just a sample and, therefore, restricted in generalizability. This applies especially to the representation of age, as our sample consists mainly of generation y, which could influence the robustness of our configurations. However, we controlled for the influence of Age in a separate post-hoc analysis (see Appendix E). The QCA approach does not aim at reaching full coverage, so there might be configurations of variables left out, such that not every patient can be mirrored in one configuration. This is, however, intended, as we aim for reliable and stable configurations in terms of coverage. Theoretically, we take the status quo bias perspective, which explains resistance as a possibility to maintain the status quo. Other studies indicate that besides behavioral resistance, there is cognitive and affective resistance, which we leave untouched within this study.

Future Research Addressing Context-Specific Theorizing in IS Research. One of the main goals of this study is to encourage future research to apply configurational approaches to context-specific theorizing in IS research and to leverage the potential from examining the interactions. Beyond that, we invite future research to apply our approach to other contextualization attempts and maybe identify general patterns of how interactions change along with contextualization.

Future Research Addressing the SQBP. Our results show that the influencing factors captured by the SQBP do not only have a separate influence, as examined in prior research, but jointly yield resistance in more complex, interdependent ways. Future research could examine the interrelations between those influencing factors in more detail with a qualitative study. Thereby, future research could reveal which influencing factors are especially important or why the negative perceptions have the power to outweigh perceived benefits. Further, future research could examine whether these interrelations are susceptible to external influences, such as group effects.

Future Research Addressing Resistance Research in Healthcare. Our results identify different configurations yielding high resistance, representing different types of patients that resist because of different influencing factors. Future research could elaborate on these patient types more by characterizing, for instance, individual differences or personality traits that characterize different patient types. This would add a more personalized attempt to resistance research in healthcare.

6 CONCLUSION

This study aims to illustrate how research can use configurational methods within the guidelines of context-specific theorizing (Hong et al. 2014) to contextualize the SQBP and eventually explain patients' resistance to using an AI-based chatbot for collecting medical data in healthcare. Therefore, we further develop those guidelines and use fsQCA to discover the role and contribution of each variable to the outcome of interest, the interplay among variables and with context-shaping factors outside the model and different instantiations of the contextualized model, represented through the equifinal configurations. We thereby contribute to context-specific theorizing in IS research by integrating configurational approaches that focus on both the contextualization of variables and the contextualization of the interplay to research treating SQBP by clarifying how and why the theoretical variables jointly lead to resistance and to the literature on AI in healthcare by explaining the gap between attested benefits and actual resistance of patients to AI-based chatbots.

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APPENDIX A: IS RESEARCH USING THE GUIDELINES OF CONTEXT-SPECIFIC THEORIZING

Paper	General theory	Context	Stage of contextualization			Analysis of separate effects vs. combined effects
			Context-sensitivity	Context-specificity	Interactions	
Aldossari and Sidorova (2020)	Extended unified theory of acceptance and use of technology (UTAUT2)	Smart home adoption	X	X		separate
Bansal et al. (2016)	Theory of reasoned action (TRA), prospect theory	Disclosure of private information online	X	X	X	separate
Benlian (2020)	Challenge-hindrance stressor framework	Technology-driven work stressors	X	X		separate
Califf et al. (2020)	Holistic stress process	Technostress with healthcare information technology	X	X		separate
Ghasemaghaei and Hassanein (2015)	IS success model	Retail and e-commerce websites	X	X	X	separate
Hung et al. (2016)	TRA	Perceive playfulness on social network sides	X	X		separate
Jaklič et al. (2018)	Information diffusion theory (IDT) and unified theory of acceptance and use of technology (UTAUT)	Business intelligence and analytics use	X	X	X	separate
Kude et al. (2018)	Resource-based view	IT governance	X	X		separate
Lowry et al. (2019)	Social learning theory, self-control theory	Cyberharassment	X	X		separate
Williams (2021)	Technology acceptance Model (TAM)	Social commerce	X	X	X	separate
Mäntymäki et al. (2014)	Decomposed theory of planned behavior	Engagement in virtual worlds	X	X		separate

Mcknight et al. (2017)	Trust theory, two-factor theory	B2B data exchange	X	X		separate
Miltgen and Smith (2019)	Privacy trade-off	Privacy disclosure	X	X	X	separate
Nelson et al. (2016)	Theory of self-regulation	Health empowerment through activity trackers	X	X		separate
Pethig and Kroenung (2019)	Social identity theory and social markedness	IS adoption of digitally disadvantaged people	X	X	X	separate
Srivastava and Chandra (2018)	Uncertainty reduction theory	Virtual collaboration	X	X	X	separate
Teng (2017)	Social capital theory	Online gaming	X	X		separate
Teng (2018)	Theory of consumption values	Online gamer loyalty	X	X		separate
Verhagen et al. (2015)	Theory of uses and gratification	Virtual customer environments	X	X		separate
Wang et al. (2019)	IS success model	Social commerce	X	X		separate
Warkentin et al. (2017)	UTAUT	Smart metering technology adoption	X	X		separate
Warkentin et al. (2016)	Protection motivation theory (PMT)	Information security	X	X		separate
Wright et al. (2017)	The technology organization-environment framework	Software as a Service	X	X		separate
Wu et al. (2018)	Professional-client interaction theory and expectation confirmation theory	Health information	X	X		separate
Wunderlich et al. (2019)	Motivation theories	Sustainable technology adoption	X	X		separate
Xiao et al. (2020)	cognitive–affective–conative–action (CACA) framework	SAAS	X	X	X	separate
Chen and Zahedi (2016)	Protection motivation theory (PMT)	Online security behavior	X	X		separate

Lee et al. (2021)	Hedonic management model of addiction	Online Role-playing game addiction	X	X	X	separate
Zahedi et al. (2015)	Protection motivation theory (PMT)	Fake website detection tools	X	X		separate

Table 7. IS Research using the Guidelines of Context-Specific Theorizing

APPENDIX B: CONSTRUCTS AND MEASURES

To develop a contextualized model, we refine the variables of the SQBP with context sensitivity and add context-specific variables to the theory. This also requires contextualization on the item level. We measured all items on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree).

To measure patients' resistance to using an AI-based chatbot for collecting medical data during anamnesis, we adapted four items from the context of enterprise IS to the resistance to using an AI-based chatbot for medical data collection. The four items represent four resistance categories: passive and covert, passive and open, active and covert, and active and open. For example, we adapted the item 'I will not cooperate with the change to the new way of working with the NOP system' to 'I will not cooperate to use an AI-based chatbot for collecting medical data during anamnesis.'

For transition costs, we adapted two items used in previous resistance studies (Polites and Karahanna 2012) by referring to the usage of an AI-based chatbot for medical data collection instead of referring to cloud software. For example, we adapted the item 'Learning how to use Google Docs to collaborate/share files with my teammates would take much time' to 'Learning how to use an AI-based chatbot for collecting medical data during anamnesis would take much time.' For uncertainty costs, in line with SQBP, we adapted three items for search and evaluation costs (Ray et al. 2012) from service providers to our context. For example, we adapted the item 'It is hard to compare the other service providers' to 'It is hard to compare my current anamnesis conducted by a 'real' physician with an anamnesis conducted by an AI-based chatbot. ' The same applies to our two items for measuring sunk costs, adapted from the context of enterprise systems (Polites and Karahanna 2012), the two items measuring anticipated regret, adapted from the context of IS investments (Lankton and Luft 2008), and three two for decisional control, adapted from the work decision context (Morgeson and Humphrey 2006). To measure loss aversion, we follow the recommendation of Lee and Joshi (2017) to assess whether patients assign greater weight to costs rather than benefits when deciding on using an AI-based chatbot for medical data collection during anamnesis. We also measured perceived benefits using five items (Kim et al. 2008)and adapted the items to our context. In line with recommendations (Lee and Joshi 2017), the calculation of loss aversion can be summarized with the following formula:

Mean (transition costs + uncertainty costs)] - perceived benefit

This means that we calculated the mean of the perceived costs, composed of transition costs and uncertainty costs, and subtracted the perceived benefits. If the mean perceived costs outweigh the perceived benefits, then loss aversion is positive, ranging from 0 to 6. Otherwise, if the perceived benefits outweigh the mean perceived costs, then loss aversion is negative, ranging from -6 to 0.

We used six items from prior literature to measure distrust in the dimensions of malevolence, deceit, and incompetence (Mcknight et al. 2017). Additionally, we included eleven items to measure disposition to change in the dimensions of short-term focus, cognitive rigidity, routine seeking, and emotional reaction (Oreg 2003).

Construct and author	Adapted item	Loadings
Benefits adapted from Kim et al. (2008)	I think using an AI-based chatbot for collecting medical data during anamnesis is convenient.	0.803
	I can improve my consultation using an AI-based chatbot to collect medical data during anamnesis.	0.849
	I can save time using an AI-based chatbot to collect medical data during anamnesis.	0.749
	Using an AI-based chatbot for collecting medical data during anamnesis enables me to inform the physician more quickly about my medical record than by talking to medical staff.	0.805
	Using an AI-based chatbot to collect medical data during anamnesis increases my productivity during the consultation.	0.908
Transition costs adapted from Polites and Karahanna (2012)	Learning how to use an AI-based chatbot for collecting medical data during anamnesis would take much time.	0.710
	Becoming skillful at using an AI-based chatbot for collecting medical data during anamnesis would be hard for me.	0.916
Uncertainty costs adapted from Ray et al. (2012)	It is hard to compare my current anamnesis conducted by a 'real' physician with an anamnesis conducted by an AI-based chatbot.	0.834
	Even when I have all the information about an AI-based chatbot, comparing my current consultation conducted by a 'real' physician to a chatbot collecting medical data during anamnesis is difficult.	0.770
	I would have to search for a lot of information to decide whether to use an AI-based chatbot for collecting medical data during anamnesis.	0.815
Sunk costs adapted from Polites and Karahanna (2012)	I have already invested a lot of time in the relationship with my physician during the consultation.	0.925
	I have already invested a lot of time establishing a good relationship with my physician (e.g., he knows all my details and memorizes them).	0.875
Anticipated regret adapted from Lankton and Luft (2008)	If I decide to use an AI-based chatbot for collecting medical data during anamnesis and it turns out to be a failure, I will regret incurring a potentially large loss in terms of treatment.	0.894
	Suppose I decide to use an AI-based chatbot for collecting medical data during anamnesis, and it turns out that the anamnesis	0.889

		complicates my medical treatment. In that case, I will regret not consulting a 'real' physician instead of the AI-based chatbot.	
Decisional control adapted from Morgeson and Humphrey (2006)		The decision to use a chatbot for collecting medical data during anamnesis allows me to use my personal initiative or judgment.	0.976
		Whether to use a chatbot for collecting medical data during anamnesis allows me to decide on my own.	0.752
Distrust adapted from Mcknight et al. (2017)	**Malevolence**	I am not sure the supplier of an AI-based chatbot collecting medical data during anamnesis would act in my best interest.	0.781
		I suspect that the supplier of an AI-based chatbot for collecting medical data during anamnesis is interested in just its own well-being, not in my well-being.	0.810
	Deceit	I am worried about whether the supplier of an AI-based chatbot collecting medical data during anamnesis would be truthful in its dealings with me.	0.870
		It is uncertain whether the supplier of an AI-based chatbot for collecting medical data during anamnesis would keep its commitments.	0.884
	Incompetence	I am skeptical about whether the supplier of an AI-based chatbot collecting medical data during anamnesis is competent and effective in providing an AI-based chatbot for collecting medical data during anamnesis.	0.823
		I feel nervous about how knowledgeable the supplier of an AI-based chatbot for collecting medical data during anamnesis is about issues of an anamnesis process.	0.910
Dispositional resistance to change adapted from Oreg (2003)	**Short-term focus**	Changing plans seems like a real hassle for me.	0.716
		Often, I feel a bit uncomfortable even about changes that may potentially improve my life.	0.767
		When someone pressures me to change something, I tend to resist it even if I think it may benefit me.	0.821
	Cognitive rigidity	Once I have concluded, I am not likely to change my mind.	0.885
		I do not change my mind easily.	0.879
	Routine seeking	I like to do the same old things rather than try new and different ones.	0.831
		I would rather be bored than surprised.	0.761
	Emotional reaction	If I were to be informed that there would be a significant change regarding how things are done at work, I would probably feel stressed.	0.816
		When I am informed of a change of plans, I tense up a bit.	0.821
		When things do not go according to plan, it stresses me out.	0.709
		If my boss changed the criteria for evaluating employees, it would probably make me feel uncomfortable, even if I thought I would do just as well without doing any extra work.	0.861
User resistance adapted from Kim and Kankanhalli (2009)		I will not comply with using an AI-based chatbot for collecting medical data during anamnesis.	0.871
		I will not cooperate with an AI-based chatbot for collecting medical data during anamnesis.	0.930
		I oppose using an AI-based chatbot for collecting medical data during anamnesis.	0.865
		I can't entirely agree with using an AI-based chatbot for collecting medical data during anamnesis.	0.891

Table 8. Constructs and Measures

APPENDIX C: COMMON METHOD BIAS

We tested for common method bias (CMB) with three tests, which all indicated that CMB does not distort our results. First, we applied Harman's single-factor test, which indicates how much of the variance in the data is explained by only one construct (Podsakoff and Organ 1986). The test reveals that one construct explained 32 percent of the variance in the data and was, therefore, below the recommended 50 percent threshold, indicating that CMB is not an issue. Second, the bivariate correlations (see Appendix D) do not show any high values, indicating that CMB is not an issue in the data set (Sharma et al. 2009). Third, we tested how much a CMB factor in a structural equation model influences the R^2 (Williams et al. 2003). The results show that adding a CMB factor to the structural equation model explains only a small additional R^2 (0.003), which indicates that CMB does not disturb the results. In summary, we can state that CMB is not an issue with our data.

APPENDIX D: DESCRIPTIVE STATISTICS

	Construct		SD	Mean	α	CR	AVE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	Benefit		1.25	5.36	0.91	0.92	0.69	0.831													
(2)	Transition cost		1.26	2.85	0.79	0.80	0.66	-0.277	0.815												
(3)	Uncertainty costs		1.51	3.90	0.85	0.85	0.65	-0.298	0.502	0.805											
(4)	Distrust	Malevolence	1.33	4.16	0.70	0.70	0.55	-0.354	0.337	0.437	0.742										
(5)		Deceit	1.41	4.12	0.88	0.88	0.79	-0.331	0.383	0.467	0.742	0.891									
(6)		Incompetence	1.47	4.26	0.93	0.93	0.81	-0.319	0.410	0.494	0.711	0.845	0.900								
(7)	Dispositional resistance	Short term focus	1.58	3.97	0.87	0.87	0.69	-0.047	0.365	0.425	0.396	0.418	0.450	0.832							
(8)		Cognitive rigidity	1.44	3.97	0.87	0.87	0.77	0.073	0.165	0.151	0.171	0.136	0.193	0.389	0.878						
(9)		Routine seeking	1.43	3.46	0.76	0.76	0.62	0.044	0.241	0.233	0.194	0.251	0.264	0.568	0.497	0.786					
(10)		Emotional reaction	1.41	4.42	0.91	0.91	0.71	-0.065	0.248	0.292	0.184	0.352	0.346	0.590	0.320	0.516	0.842				
(11)	Sunk costs		1.68	4.37	0.92	0.93	0.88	-0.208	0.197	0.267	0.195	0.208	0.276	0.110	0.093	0.093	0.127	0.935			
(12)	Anticipated regret		1.21	5.58	0.86	0.86	0.68	-0.251	0.245	0.345	0.303	0.358	0.500	0.280	0.018	0.070	0.265	0.211	0.822		
(13)	Decisional control		1.21	5.50	0.85	0.86	0.75	0.355	-0.175	-0.027	-0.101	-0.037	-0.068	-0.101	-0.084	-0.060	0.002	0.147	0.197	0.876	
(14)	Resistance		1.44	4.46	0.09	0.90	0.75	-0.469	0.460	0.541	0.583	0.562	0.595	0.363	0.059	0.098	0.252	0.320	0.447	-0.048	0.868

Table 9. Descriptive Statistics Sample 1 - Anamnesis

APPENDIX E: FSQCA APPROACH

To analyze which configurations of the variables from our contextualized model extracted from SQBP and context-shaping factors outside the model lead to a patient's resistance to AI-based chatbots for collecting medical data during anamnesis, we take a configurational approach (El Sawy et al. 2010; Misangyi et al. 2017) and use fuzzy-set qualitative comparative analysis (fsQCA). FsQCA primarily reveals sufficient configurations associated with an individual's resistance, but fsQCA does not focus on identifying the net effect of the single influencing factors (Ragin 2009). Within this configuration, the influencing factors can either be present or absent. The data analysis consists of five steps. First, the **calibration** of the survey data into fuzzy sets; second, the analysis of **sufficient configurations of influencing factors** leading to patients' resistance to AI-based chatbots for collecting medical data during anamnesis; and third, the analysis of **necessary influencing factors**. Finally, we tested the **robustness of the results**. For all steps, we use the QCA R package (Duşa 2018) and the fsQCA 3.0 software (Ragin et al. 2016).

For the **calibration,** we transformed the interval scale values (1 = "strongly disagree," 4 = "neither agree in nor disagree," 7 = "strongly agree") of the influencing factors and the value measuring a patient's resistance into fuzzy sets. In line with the QCA literature (Fiss 2011; Misangyi et al. 2017), we used the direct calibration for the survey data using three qualitative anchors (value 1 for full non-membership; value 4 for the crossover point, value 7 for full membership). For loss aversion (see Appendix B), we used the values -5, 0, and + 5. For the second analysis, we additionally integrated the frequency of medical consultations per year. To calibrate the frequency of consultations per year into the fsQCA analysis, we based on the fact that most people have between three and five consultations per year (Habekuß 2019) and used 4 as the crossover point, two as the anchor for full non-membership and value 6 for the full membership in the set 'high frequency of medical consultations.' Through this calibration, we transformed the values into fuzzy-set values used in the next steps.

A **sufficient configuration of influencing factors** is a bundle of factors leading to an individual's resistance. In other words, patients will respond with resistance every time a sufficient configuration of influencing factors exists. In both analyses, we analyzed for sufficient configurations. To conduct the analysis, we first construct the truth table resistance to AI-based chatbots for collecting medical data during anamnesis, which lists all possible configurations of the influencing factors. Because we have eight (analysis part 1) and nine (analysis part 2) influencing factors, the truth tables consist of 2^k configurations, with k being the number of influencing factors. Thus, the truth table shows 256 and 512 possible configurations. Second, we apply a recommended frequency threshold (n=3), consistency threshold (consistency = 0.85), and PRI consistency threshold (PRI consistency = 0.85) to reduce the truth table to sufficient configurations (Ragin 2009). This means that all configurations that do not represent at least four observations with a lower consistency than 0.85 and a lower PRI consistency than 0.85 are excluded from further analyses. The reduced truth tables are displayed in Table 10 and Table 11. Finally, we apply the Quine-Mc-Cluskey algorithm to minimize all sufficient configurations and identify core and peripheral conditions (Ragin 2009). The conditions in the simple solution, which also appear in the intermediate solution, are core conditions strongly related to the outcome. On the other hand, the conditions only included in the intermediate solution are peripheral conditions with a fairly weak relationship to the outcome and complement the core elements to produce the outcome (Fiss 2011).

Necessary influencing factors are influencing factors that need to exist if patients show resistance to AI-based chatbots for collecting medical data during anamnesis. In both analyses, we analyzed for necessary influencing factors. To be considered necessary, the influencing factor must exceed the recommended consistency threshold of 0.90, coverage threshold of 0.60, and relevance of necessity threshold of 0.60 (Mattke et al. 2021; Ragin 2006; Schneider and Wagemann 2010).

We conducted several tests for the second analysis to test for the robustness and validation of the results. We test the results for robustness. As the calibration of the survey data into fuzzy sets is an important determinant for the results, we follow prior QCA literature and test for robustness to calibration (Maier et al. 2021a; Park et al. 2017). We tested whether the results were stable to two different calibrations. In the first robustness test, we assessed whether the results were stable if we used a lower threshold for being fully in and out of a set. This means we transformed the maximum Likert scale value to a 0.95 fuzzy value and the minimum Likert scale value to a 0.05 fuzzy set value, the threshold for full membership (Ragin et al. 2016). In the second robustness test, we tested whether the results were stable if we used higher thresholds for fully in and fully out of a set. Here, the fuzzy score of 1.00 is already at the Likert scale value of 5.5, and the fuzzy score of 0.00 is already at the Likert scale value of 2.5.

In line with recent QCA literature (Pappas and Woodside 2021), we also tested for the predictive validity of the QCA results. This means that we tested our QCA model on a test dataset that has not been used for developing the QCA model. We used the same data collection approach described above and sampled 100 participants for the test dataset. We then followed previous guidelines (Pappas and Woodside 2021) and analyzed the overall consistency of the QCA model on the test dataset. For this, we created a new condition with logical operators that reflects the QCA model from analysis part 2. We then analyzed the consistency of this new condition with the outcome.

Transition cost	Uncertainty costs	Loss aversion	Sunk costs	Anticipated regret	Decisional control	Distrust	Dispositional resistance	Number	Resistance	Raw consist.	PRI consist.
1	1	1	1	1	1	1	1	12	1	0.99	0.98
1	1	1	1	1	1	1	0	3	1	0.99	0.97
1	1	1	0	1	1	1	0	3	1	0.99	0.94
1	1	0	1	1	1	1	1	8	1	0.98	0.93
0	1	0	1	1	1	0	1	6	1	0.97	0.92
0	1	0	1	1	1	1	1	12	1	0.96	0.89
1	1	0	1	1	1	1	0	4	1	0.97	0.89
0	1	0	1	1	1	1	0	8	1	0.95	0.85
0	1	0	1	1	1	0	0	7	0	0.94	0.78
0	1	0	0	1	1	1	1	8	0	0.93	0.77
0	0	0	1	1	1	1	1	9	0	0.89	0.68
0	0	0	1	1	1	1	0	13	0	0.88	0.66
0	1	0	0	1	1	0	0	6	0	0.91	0.62
0	0	0	1	1	1	0	1	3	0	0.88	0.55
0	0	0	0	1	1	1	1	3	0	0.89	0.55
0	0	0	1	1	1	0	0	14	0	0.79	0.41
0	0	0	0	1	1	0	1	7	0	0.80	0.30
0	0	0	0	1	1	0	0	8	0	0.76	0.28
0	0	0	0	0	1	0	0	3	0	0.86	0.23
0	0	0	1	0	1	0	0	4	0	0.85	0.20
Note: We mark configurations that exceed the thresholds for sufficiency with the value 1 in the column 'resistance.'											

Table 10. Analysis Part 1 Truth Table

Transition cost	Uncertainty costs	Loss aversion	Sunk costs	Anticipated regret	Decisional control	Distrust	Dispositional resistance	High frequency	Number	Resistance	raw consist.	PRI consist.
1	1	1	1	1	1	1	1	0	9	1	1.00	0.99
1	1	1	1	1	1	1	1	1	3	1	1.00	0.99
1	1	1	0	1	1	1	0	0	3	1	0.99	0.96
1	1	0	1	1	1	1	1	0	5	1	0.98	0.95
1	1	0	1	1	1	1	1	1	3	1	0.98	0.95
0	1	0	1	1	1	0	1	1	3	1	0.98	0.93
1	1	0	1	1	1	1	0	0	3	1	0.97	0.91
0	1	0	1	1	1	1	1	0	9	1	0.96	0.90
0	1	0	1	1	1	0	1	0	3	1	0.97	0.90
0	1	0	1	1	1	1	1	1	3	1	0.96	0.89
0	1	0	1	1	1	1	0	0	7	1	0.95	0.86
0	1	0	0	1	1	1	1	0	6	0	0.95	0.81
0	0	0	1	1	1	1	0	1	3	0	0.95	0.80

0	1	0	1	1	1	0	0	0	6	0	0.93	0.78
0	0	0	1	1	1	1	1	1	3	0	0.94	0.77
0	0	0	1	1	1	1	1	0	6	0	0.90	0.68
0	1	0	0	1	1	0	0	0	4	0	0.91	0.65
0	0	0	1	1	1	1	0	0	10	0	0.87	0.61
0	0	0	1	1	1	0	0	1	5	0	0.89	0.54
0	0	0	1	1	1	0	0	0	9	0	0.82	0.42
0	0	0	0	1	1	0	1	0	4	0	0.85	0.40
0	0	0	0	1	1	0	0	0	5	0	0.79	0.34
0	0	0	0	1	1	0	1	1	3	0	0.84	0.30
0	0	0	0	1	1	0	0	1	3	0	0.84	0.29
0	0	0	1	0	1	0	0	0	4	0	0.85	0.22
Note: We mark configurations that exceed the thresholds for sufficiency with the value 1 in the column 'resistance.'												

Table 11. Analysis Part 2 Truth Table

Post-hoc Analysis: Influence of Age

Looking at the sample characteristics, we see that the sample represents relatively young participants with a mean age of 34.04 (see Table 4). When looking at the age from a generation perspective, we see that almost 73 percent of our participants are categorized as Generation Y, thus born between 1981 and 2012. To see whether the age of the participants influences our results, we analyzed the average portion of each generation in each sufficient configuration. We see that the results are particularly relevant for Generation Y. Moreover, we see no specific configurations that reflect specific patterns of the baby boomer generation Generation X.

	Baby Boomer in percent	**Generation X in percent**	**Generation Y in percent**
Entire sample	6.25	20.00	73.86
C1	5.56	11.11	83.33
C2	5.26	15.79	78.95
C3	0.00	12.50	87.50
C4	0.00	0.00	100.00

Table 12. Influence of Age

Paper VIII

Artificial Intelligence in Healthcare:

A Mixed Methods Study of Physicians' Chatbot Adoption Decision

Lea Reis
University of Bamberg

Christian Maier
LMU Munich School of Management, Ludwig-Maximilians-Universität München

Lea Reis
University of Bamberg

Tim Weitzel
University of Bamberg

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Artificial Intelligence in Healthcare: A Mixed Methods Study of Physicians' Chatbot Adoption Decision

ABSTRACT

Drawing on theories on information processing and IS adoption, we theorize and validate a three-stage processing yielding the intention to adopt healthcare AI: decomposition, integration, and causation. In the decomposition phase, we identify the enablers and inhibitors of the AI adoption intention. In the integration phase, we examine which configurations of AI enablers and inhibitors lead to a high or low intention to adopt with a QCA study. For the causation phase, we derive dominant constellations and use interviews to explain why the physicians perceive them as dominant. We integrate a configurational and a qualitative study into a meta-analysis and validate our theorizing with an additional post-hoc study with an external sample.

We contribute to IS and AI adoption research by offering a three-stage approach to the underlying processing that forms the intention to and characterizes AI adoption. We further contribute to AI adoption in healthcare settings by identifying seven contextually relevant enablers and inhibitors shaping the intention to adopt AI and elaborating on specific configurations yielding a high or low intention to adopt.

Keywords: Qualitative comparative analysis (CA), mixed methods, cognitive agents, enablers and inhibitors, information processing, decision-making

1 INTRODUCTION

Recent practical studies highlight the benefits of integrating artificial intelligence (AI) into business, including the optimization of processes and workflows and better resource allocation (e.g., Brynjolfsson and Mitchell 2017; Davenport and Ronanki 2018; Tarafdar et al. 2019). The degree to which these benefits can be achieved depends on users' adoption of AI. Creating AI adoption is difficult and influenced by many characteristics, such as the invasiveness of the change the AI integration depicts for existing processes and workflows (Tarafdar et al. 2019) and the complexity of the process the AI should be integrated with (Brynjolfsson and Mitchell 2017).

A good example is the integration of AI into existing support systems like customer relationship management (CRM) systems supporting customer interaction (HBR Analytic Services 2019; Shih 2016). For users of such support systems, the benefits of integrating AI support are easy to recognize when the AI helps get better results or relieves workers from routine tasks, improving the old and well-known processes. But things become more difficult when the AI changes fundamental aspects of work or is used for more complex processes. For example, if a salesperson normally consults the CRM to find out about customer history and then uses the data to think about possible sales leads, automation of the decision process, such that the AI directly suggests promising sales leads, may be perceived as advantageous. Yet, if the new AI-supported CRM is designed automatically to engage in customer interaction, the salesperson might be less inclined to accept the new AI-powered system.

Industries that cannot even retort to well-established support systems find it even more difficult to create AI acceptance through performance expectancy, and AI is likely to face less adoption (Tarafdar et al. 2019). Healthcare is an example of such an industry that faces a cold start on AI. Instead of integrating information systems (IS) into basic processes, as with Electronic Health Records (EHR) and digital workflows, most paperwork in healthcare is exactly what the name implies – paperwork (Monica 2019; Peng et al. 2014). Because of the lack of established support systems in hospitals, the benefits of AI support are more difficult to appreciate and more likely to change than just some supporting tasks. Therefore, we argue that implementing AI in hospitals is perceived as much more radical and invasive by many stakeholders, and hence faces more resistance, making AI adoption much less likely (Tarafdar et al. 2019). This is especially true when the AI is integrated with complex processes (Davenport and Ronanki 2018) involving multiple data sources, users, important decisions, and interdependent process steps.

An example of such a complex process in healthcare is the anamnesis-diagnosis-treatment-documentation process in hospitals. In this process, the physician interacts with the patient to collect data on the patient's medical history during anamnesis, integrates this data with the patient's EHR to decide on a diagnosis, based on which the physician recommends treatment, and finally documents everything into the EHR system. Implementing an AI — for example, a cognitive agent that automates the documentation of anamnesis, diagnosis, and treatment, delivers decision support for the diagnosis, and directly engages with physicians and patients — constitutes an invasive change for the established workflows and technologies. Therefore, for the AI adoption decision, AI perceptions of different stakeholders and their interactions are relevant, including physicians and patients (Shaffer et al. 2013), as physicians' attitude towards AI rests on how their own working routines are affected but also their patients' safety and survival (Payton et al. 2011). Further, these considerations are interdependent and need to be assessed in their importance to make an adoption decision. For example, the perception of the cognitive agent offering a relative time advantage that reduces the physicians' workload would probably be less important than the perception of lacking trust and risking patients' safety.

Besides the degree of invasiveness concerning AI integration and the complexity of the process the AI is integrated with, this highlights a third characteristic shaping AI adoption: the potential trade-off between AI consequences for the different stakeholder groups, which leads to an assessment of importance regarding the perceptions and their potential in yielding a certain consequence. As physicians cannot process all these perceptions and potentials separately, forming an AI adoption decision in healthcare is particularly complex (Furnari et al. 2020). Existing theories in IS research (e.g., Ajzen and Fishbein 1980; Davis 1989; Venkatesh et al. 2003) focus on relevant technological and social perceptions of the IS, not yet AI, and how they impact an individual's intention to adopt. However, taking the three characteristics shaping AI adoption into account, we see that the applicability of these theories to describe AI adoption is limited. First, they currently do not account for AI-specific perceptions, for example, perceptions concerning an interaction with users or explainability of the AI's decisions or predictions. Second, perceptions are theorized to have an independent and separate influence on an individual's intention to adopt existing theories (Furnari et al. 2020; Sussman and Siegal 2003), leaving a possible analysis of interdependent perceptions untouched. Third, they were not designed to include the potential trade-off between consequences, resulting in an assessment of the importance of perceptions compared to other intertwined perceptions that come with the adoption decision. However, understanding the processing of interdependent perceptions and their importance is decisive to understanding complex adoption decisions, such as physicians' adoption decision of a cognitive agent in healthcare, respecting the associated perceptions and their potential to yield consequences for physicians and patients. As existing IS adoption theories do not allow us to theorize and understand AI adoption fully, we cannot leverage them in our study.

In that respect, this study suggests an alternative approach for examining the processing forming the intention to adopt. We use the example of a cognitive agent implemented into the anamnesis-diagnosis-treatment-documentation process in hospitals. Based on existing research on complex decision-making (Campbell et al. 2016) and information processing (Zadeh 1983), we suggest a three-stage processing in forming the intention to adopt, with invasive AI integrations into complex processes, demanding a trade-off of AI consequences. Theorizing this three-stage processing in forming the intention to adopt allows us to understand the relevant perceptions of the AI, here the cognitive agent, their simultaneous processing as an interdependent whole, and their assessment of importance regarding potential consequences of the AI integration.

In the course of this study, we first present the existing knowledge of healthcare and IS adoption, followed by existing research treating AI integration and AI adoption. Then, we present the theorizing of the processing forming the intention to adopt AI, here the cognitive agent, based on complex decision-making and information processing. Our suggested processing is empirically validated by a mixed-methods approach, consisting of a configurational Study 1 and a qualitative Study 2. We integrate both studies into a meta-analysis and validate our theorizing with an additional post-hoc study with an external sample. We integrate the insights from both studies and discuss the contributions to research treating cognitive agents, IS, and AI adoption research. We provide recommendations for hospitals and healthcare providers.

2 THEORETICAL BACKGROUND

To examine the processing forming physicians' intention to adopt AI, here a cognitive agent, we first provide insights into the research context, integrating prior research on information systems and cognitive agents in healthcare and insights on how AI adoption exceeds the scope of IS adoption research.

2.1 IS Adoption in Healthcare

Healthcare is among the industries that cannot draw upon a long history of IS integration, as most healthcare facilities have not seen any necessity for strategic IS initiatives (McKinsey 2019). Five years ago, only 44 percent of all hospitals had adopted a basic support system to take in new patients, and only one in eight had implemented an EHR system to manage patients' data (Peng et al. 2014). Today, 97 percent of hospitals have integrated a working EHR system (Monica 2019). Still, only a few have engaged in other IS implementations to improve care provision, such as clinical decision support systems or telehealth (Reddy 2019). Although such support systems are associated with rather directly observable benefits and, at the same time, could enable hospitals to address the rising demand for healthcare much better, especially during a pandemic like we experienced a few years ago (Yaraghi 2020), the IS adoption within this industry has happened slower than desired (Agarwal et al. 2010). Disturbingly, IS adoption has been so slow that industry reports estimate that, barring significant changes in their IS infrastructure, most healthcare facilities will not be able to cope with the increasing healthcare demands in the future (McKinsey 2020) and that only 22 percent are equipped to handle current demand (Gartner 2019).

This development is also reflected by recent literature treating IS adoption in healthcare. Most papers treat elements of adopting an electronic health record (EHR) system, but few studies other IS (see Table 1). Existing work repeatedly stresses the idiosyncrasy of the healthcare environment (e.g., Pinsonneault et al. 2017), where the pace of adoption and diffusion of IS stays below a rising demand for healthcare (Agarwal et al. 2010; Peng et al. 2014). One reason is that physicians must simultaneously process various considerations when deciding whether to adopt a new IS(Pinsonneault et al. 2017). Prior research treating IS adoption in healthcare suggests three considerations affecting physicians' adoption decisions. First, the perceptions regarding the physicians' assessment of the IS (e.g., Ayal and Seidman 2009). Second, perceptions concerning the assumed patient reaction (Yaraghi 2020). Third, the potential to yield consequences on physicians' working routines, treatment quality, and patients' safety (e.g., Pinsonneault et al. 2017) (see Table 1). Simultaneously processing all these considerations is complex, as the physicians are not only forced to integrate all this information but because different perceptions shaping the adoption decision are interdependent, building boundaries for each other or coexist to have an influence and cannot be processed separately (Liu et al. 2017; Straatmann et al. 2018). Further, the potentials to yield certain positive and negative consequences related to the adoption of the IS need to be assessed as less or more dominant. For example, physicians would value a potential risk for patients' safety as dominant than a possible relative time-advantage in the treatment process through the IS (Keeffe et al. 2005), which complicates the processing in forming the intention to adopt.

Paper	Information system	Perspective		Consideration of potentials	Major findings
		Physicians	Patients		
Adjerid et al. (2018)	EHR			X	Financial incentives and mature systems have a positive effect on decrease
Agarwal et al. (2010)	EHR	X	X	X	Adoption guidelines
Angst and Agarwal (2009)	EHR		X		Privacy Concerns in EHR adoption, Elaboration
Ayabakan et al. (2017)	EHR			X	Data sharing reduces duplications in medical data
Ayal and Seidman (2009)	EHR	X			Satisfaction of employees was raised through EHR
Baird et al. (2017)	EHR			X	Long-term assimilation of processes and administration
Bernardi (2017)	EHR		X	X	HealthIT can foster human development and healthcare
Bhattacherjee and Hikmet (2007)	EHR	X			Distrust as a driver of adoption failure
Brohman et al. (2019)	Telehealth		X		Feedback from patients is valuable for telemonitoring
Doolin (2004)	EHR	X			Disclosure depicts a problem
Findikoglu and Watson-Manheim (2016)	EHR	X		X	Linkage of macro-level goals and micro-level behavior is needed to enable adoption in developing countries
Holden and Karsh (2010)	EHR	X			Established models are not sufficient for healthcare
Jensen et al. (2009)	EHR		X		Implications for field, organization, and individual cooperation
Kane and Labianca (2011)	EHR	X			IS avoidance risks the implementation success
Klecun et al. (2019)	EHR	X			Stakeholder integration is difficult. Top-down attempt necessary
Kohli and Tan (2016)	EHR	X			Stakeholders' issues that must be addressed to develop and deploy EHR.
Kwon and Johnson (2018)	EHR			X	Meaningful-use fosters security performance
Lin et al. (2017)	EHR			X	Multitask approach recognizes multiple adverse effects in chronic diseases
Lin et al. (2019)	EHR			X	Meaningful use and readiness of processes positively affect the quality
Mantzana et al. (2007)	EHR	X			Adoption is not easy, as it affects patients' lives, actors are important.
Mettler et al. (2017)	Service robots	X			Applications for robots and staff reactions to innovation
Mishra et al. (2012)	EHR	X			Physician identity fosters assimilation
Murungi et al. (2019)	Data interchange	X			Distrust in the system limits adoption
Nov and Schecter (2012)	EHR	X			Physicians show a dispositional resistance to change to EHR

Ozdemir et al. (2011)	EHR			X	Personal EHR can provide benefits as they do not have switches in systems
Peng et al. (2014)	EHR	X			Slow healthcare IS adoption
Pinsonneault et al. (2017)	EHR			X	Quality improvement and cost reduction
Raman and Grover (2020)	EHR	X			Cohesiveness vs structural holes in effect of adaptation.
Reardon and Davidson (2007)	EHR			X	The inclusion of small practices enables the full benefits of EHR
Silsand and Ellingsen (2014)	EHR	X			Participation of personal in implementation fosters use
Strong et al. (2014)	EHR	X			Affordance-based change management for multilevel process change
Tong et al. (2017)	EHR	X			Social power and administrative work shape indirect use
Yaraghi et al. (2015)	Data inter-change			X	Adaption use and value co-production of data sharing
Yaraghi et al. (2019)	Data inter-change		X		Patients do not solely trust their physician in disclosing

Table 1. IS Adoption in Healthcare

2.2 AI Adoption in Healthcare

The most promising opportunity for healthcare to compensate for rising demands in healthcare is the integration of AI into time- and personnel-intensive processes (McKinsey 2020), such as the anamnesis-diagnosis-treatment-decision process. Thereby, the physician interacts with the patient to collect data on his medical history during anamnesis, integrates this data with the patient's EHR to decide on a diagnosis, based on which the physician recommends treatment, and finally documents everything into the EHR system. An AI could automate the documentation of anamnesis, diagnosis, and treatment, deliver decision support for the diagnosis, and directly engage with physicians and patients, reducing process time and costs and increasing treatment quality. As implementation costs are a barrier to implementation in the healthcare context, and the relevant quality dimensions are time and treatment quality (Agarwal et al. 2010), often, all three components are combined within one cognitive agent to cut implementation costs and to realize benefits (McKinsey 2020).

Cognitive agents combine machine learning and natural language processing to build engaging, completely virtual entities capable of executing tasks, communicating, and learning from data sets to make decisions and predictions (Davenport and Ronanki 2018). Early agents like ELIZA had only rudimentary abilities to participate in conversations based on simple decision trees (Schuetzler et al. 2014). Cognitive agents nowadays steadily improve their capability to imitate human-to-human interaction by using natural language processing, pattern matching, and machine learning (Al-Ramahi and Noteboom 2018; Brynjolfsson and Mitchell

2017). Using those communication abilities and based on machine learning, cognitive agents can assist in or automate tasks involving direct engagement, reduce costs, increase quality, and optimize personnel- and time-intensive processes.

Prior research treating AI implementations in healthcare (Comendador et al. 2015; Denecke et al. 2018; Longoni et al. 2019; Oh et al. 2017) has so far focused on sensible use cases for AI but did not elaborate on the adoption of AI in particular. The few insights provided indicate that physicians have to include three types of considerations analogous to the adoption of other IS in healthcare (see Table 1): First, their own perceptions of the new IS and the AI. Second, possible perceptions of patients (Shaffer et al. 2013). Third, the potential of these perceptions regarding the consequences of the adoption for physicians' working routines and patients' safety and survival (Payton et al. 2011). Those considerations are interdependent and simultaneously influence physicians' decision to adopt AI. Implementing cognitive agents that physicians could use to delegate individual tasks within the anamnesis-diagnosis-treatment-documentation process depicts an invasive change in the established workflows due to the lack of existing support tools possibly integrating AI. We know from other contexts that an invasive change and complex processes lower employees' intention to adopt AI (Brynjolfsson and Mitchell 2017; Tarafdar et al. 2019), which makes it even more important to examine physicians' decision whether to adopt the cognitive agent more closely.

2.3 AI Adoption and IS Adoption Theories

So far, prior research has not theorized the adoption of cognitive agents. Still, recent observations in literature considering meaningful use cases for AI in healthcare (Denecke et al. 2018) and other industries (e.g. Rai 2020) indicate that the physicians' adoption of AI, here the cognitive agent, is shaped by three characteristics. First, the degree of invasiveness concerning AI integration. Suppose the degree is high due to lacking support systems. In that case, there is a need to simultaneously process perceptions concerning the IS and AI-specific perceptions. In contrast, when the degree is low, only the AI-specific perceptions need to be processed, as the system integrating the AI is already known. Second, the degree of complexity of the process selected for the AI implementaion. If the degree is high, this leads to interdependent perceptions concerning the physicians, the patients, and the potential to yield consequences for both perspectives that need to be processed as one. If the degree is low, the perceptions can be treated separately. Third, the degree of potential trade-off between AI consequences. If the degree is high, this results in an assessment of the importance of perceptions compared to other intertwined perceptions that come with the adoption decision. If the degree is low, an assessment is not needed.

Suppose the degree of invasiveness, complexity, and potential in yielding consequences of the AI adoption is high, for example, with adopting a cognitive agent for the anamnesis-diagnosis-treatment documentation process. In that case, the adoption decision is complex, as these perceptions cannot be processed separately (Furnari et al. 2020). Whereas an AI adoption with a low degree of characteristics could possibly be theorized with existing IA adoption theories, a high degree imposes limitations on the applicability of these theories.

Existing IS adoption theories (e.g., Ajzen and Fishbein 1980; Davis 1989; Venkatesh et al. 2003) consider relevant perceptions of the IS, such as ease of use and perceived usefulness, and social characteristics, such as image, and do not cover these AI-specific perceptions, for example, related to the ability to engage in human-like interactions (Rzepka and Berger 2018) and to report interpreted data (Rai 2020). Absent this knowledge, we cannot understand the perceptions that go beyond the existing concepts of technology adoption, such as perceptions related to the interaction with users or perceptions related to the interpretation, not just the processing, of data (e.g. Rai 2020).

Further, from a theoretical perspective, the interdependence of perceptions related to the cognitive agent influencing their decision to adopt and the assessment of dominant potentials in yielding consequences exceeds the power of existing theories. So far, IS perceptions are theorized to have an independent and separate influence on individuals' intention to adopt (Furnari et al. 2020; Sussman and Siegal 2003). Despite offering valuable insights, these theories are neither designed to answer questions about the processing of perceptions in deciding to adopt new IS (Sussman and Siegal 2003), here the cognitive agent nor to explain adoption as a consequence of interdependent perceptions, processed simultaneously (Furnari et al. 2020) and prioritized in their potential to yield consequences for the individual and others. However, understanding the processing of interdependent perceptions and their importance is decisive to understanding complex adoption decisions, such as physicians' adoption decision of a cognitive agent in healthcare, respecting the associated perceptions and their potential to yield consequences for physicians and patients. As existing IS adoption theories do not allow us to fully theorize and understand AI adoption, we cannot leverage them in our study (see Table 2).

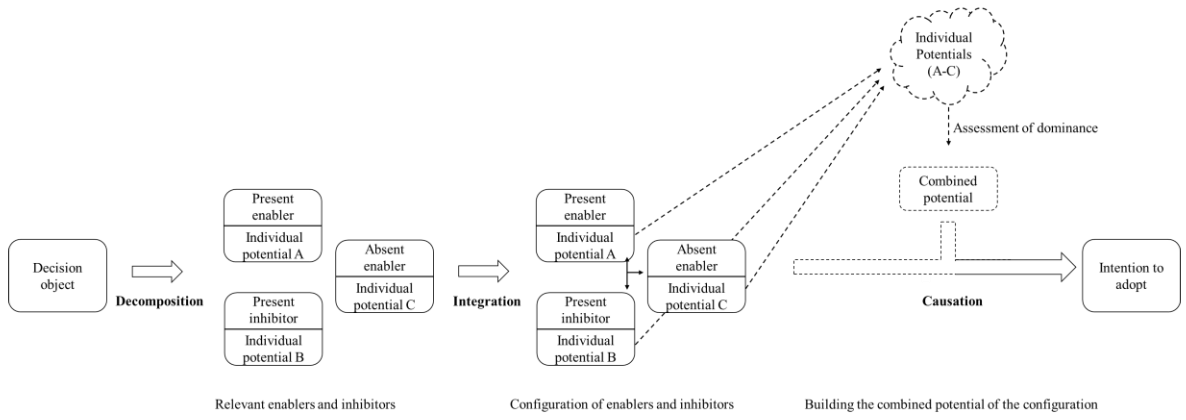
Characteristics of AI adoption	Degree of characteristics of AI adoption		Covered by IS adoption theory?
Invasiveness of AI integration	High	*No existing support systems, the user has to process perceptions of the IS and AI-specific perceptions simultaneously*	
	Low	Support system exists, the user has to process only AI-specific perceptions	(x)
Complexity of process the AI is integrated in	*High*	*Multiple users, data sources, decisions, and consequences*	
	Low	One perspective, simple process structure	x
Potential trade-off between AI consequences	*High*	*Interdependent considerations for all users and assessment of the importance of perceptions compared to other perceptions*	
	Low	Separate perceptions yielding separate consequences	x
Note: Text in italics indicates the degree of the characteristics of AI adoption that apply to this study. (x) indicates that it possibly could be covered by current IS theories, for example, TAM (Davis 1989)or UTAUT (Venkatesh et al. 2003), but so far is not.			

Table 2. Summary of Characteristics of AI Adoption and their Coverage by IS Theory

In that respect, this study suggests an alternative approach for examining the processing of perceptions forming the intention to adopt AI, respecting interdependent perceptions and their potential to yield consequences for physicians and patients and prioritizing these potentials in forming the intention to adopt AI. Existing research offers the concept of enablers and inhibitors, defined as perceptions attributed with a certain potential to influence the intention to adopt, respecting the resulting consequences (Cenfetelli 2004). These enablers and inhibitors can be present or absent. Present enablers are attributed with the potential to foster the intention to adopt, and absent enablers have the potential to hinder the intention to adopt. Present inhibitors are attributed with the potential to hinder the intention to adopt, whereby the potential of absent inhibitors does not have an influence (Cenfetelli and Schwarz 2011). To examine physicians' processing of enablers and inhibitors related to the cognitive agent, respecting the interdependence of enablers and inhibitors and the prioritization of the potentials in forming the intention to adopt, we base on existing research on complex decision-making (Campbell et al. 2016) and information processing (Zadeh 1983) and suggest a three-stage processing forming physicians' intention to adopt. Theorizing this three-stage processing in forming the intention to adopt allows us to understand the relevant enablers and inhibitors related to the cognitive agent, their simultaneous processing as an interdependent whole, and their assigned potentials influencing the intention to adopt AI depending on their prioritization.

3 THEORY BUILDING: THEORIZING THE PROCESSING FORMING THE INTENTION TO ADOPT AI

With complex decision-making, the decider has to integrate various variables with interdependencies and assess the consequences of the decision for himself and others within a manageable amount of time (Meyer et al. 2014). Therefore, deciders have to find a trade-off between decision accuracy and decision speed (Dane and Pratt 2007). Consequently, they must aggregate information in a heuristic approach, building aggregated patterns that capture the decision object more quickly and holistically (Campbell et al. 2016). The higher the deciders perceived a lack of control in handling all aspects of the decision, the more the human brain relies on aggregated patterns, serving as a compensatory control mechanism (Whitson and Galinsky 2008). This holistic approach based on aggregated patterns reflects a configurational approach (Dane and Pratt 2007), where the perceptions formed about the decision object, here the cognitive agent, are products of interdependent interactions among multiple perceptions. This theorizing is also supported by research in neuroscience, indicating that intentions are formed based on the recognition and combination of multiple factors and features (Pelli and Tillman 2008). In more detail, this means that the physician no longer considers every possible consideration related to the decision to adopt the AI, here the cognitive agent. Instead, the physician aggregates the most relevant enablers and inhibitors, capturing the physicians' and the patients' perspectives on the cognitive agent and their attributed potential in delivering positive and negative consequences to a cohesive whole. This cohesive whole is represented by a configuration of enablers and inhibitors processed as one while forming the intention to adopt (Pelli and Tillman 2008). T processing happens in three sequential phases - decomposition, integration, and causation (Campbell et al. 2016) (see Figure 1).



The three-staged processing happens within one attempt in the human brain. Dashed lines and objects represent processes that are theorized, but not included into the measurement model but examined qualitatively.

Figure 1. Processing Forming the Intention to Adopt AI

To better understand the theorized processing and the related key concepts, we provide a glossary with a short explanation and the input and output where appropriate in Appendix A. In the following, we present the processing contextualized to adopting a cognitive agent in healthcare, where the cognitive agent serves as the decision object processed in three sequential phases, forming physicians' intention to adopt AI.

3.1 Decomposition

In the **decomposition** phase, the human brain decomposes the decision object, here the cognitive agent, into a limited number of enablers and inhibitors that are relevant to it (Campbell et al. 2016). Enablers and inhibitors are perceptions with individual potential to bring about the consequences in terms of goals, commitments, or values related to the adoption (Cenfetelli and Schwarz 2011). For example, a physician could intend to adopt a cognitive agent to speed up patient treatment. In this case, the perception of a relative time advantage of the cognitive agent has a positive individual potential to bring about that consequence to speed up patient treatment and, therefore, has the individual potential to foster the intention to adopt the cognitive agent (see Figure 2).

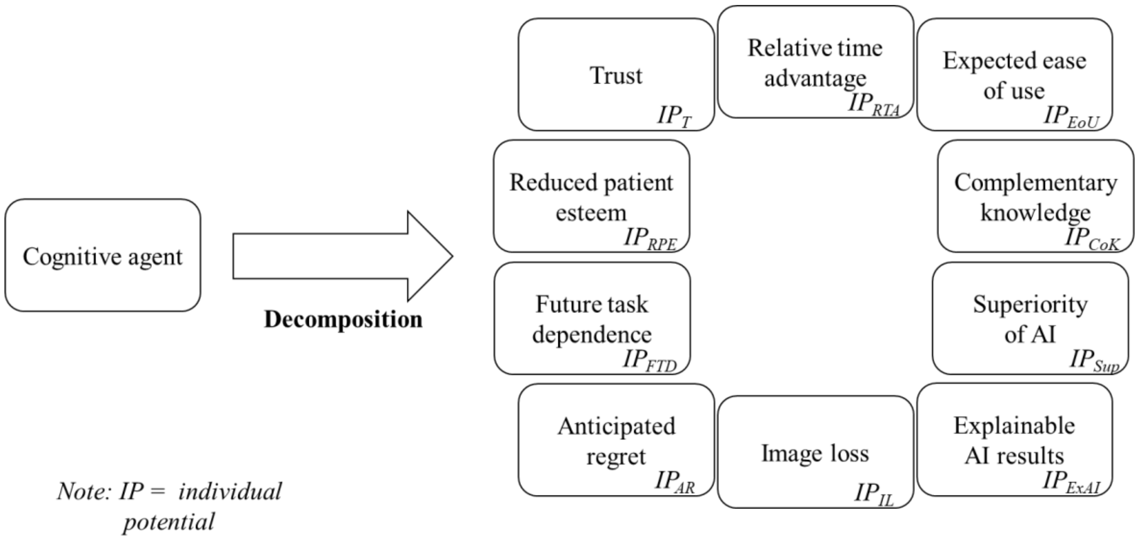


Figure 2. Decomposition into Relevant Enablers and Inhibitors Attributed with Individual Potentials (IP) Influencing the Intention to adopt AI

Enablers and inhibitors are qualitatively different, and one is not the opposite of the other (Cenfetelli 2004). To identify relevant enablers and inhibitors related to physicians' adoption of cognitive agents, we leveraged insights from prior research indicating that physicians, when deciding whether to adopt AI, integrate their perceptions of the IS and AI-specific perceptions, assumed perceptions of the patients and possible consequences resulting from the adoption (see Table 1). Therefore, we consulted literature treating the adoption of support systems in healthcare (Longoni et al. 2019; Shaffer et al. 2013), the adoption of decision support tools in IS (Komiak and Benbasat 2006), human-computer interaction (Hinds et al. 2004) and the adoption of AI-enabled systems (Rai 2020; Siau and Wang 2018) (see Table 3) to identify relevant enablers and inhibitors related to the IS and the AI describing the perspective of physicians and patients and the potentials to yield consequences of an AI adoption.

We learn that *Trust* is especially important because the decisions of the cognitive agent have the potential for highly consequential and life-threatening outcomes (Botti and Iyengar 2006). Physicians must trust the cognitive agent and its competence, integrity, and benevolence toward the patient (Komiak and Benbasat 2006). Further, when adopting any computerized support tools in healthcare, physicians primarily aim at increased efficiency through a *relative time advantage* (Longoni et al. 2019), as they want to free time for patients' treatment. Furthermore, for time-saving reasons, physicians expect *ease of use* in handling the support tools because this reduces the effort in learning how to use the support tool (Gombolay et al. 2018). Also, if physicians perceive the AI as at least equally competent, they use the AI as a valuable second opinion to gain *complementary knowledge* (Siau and Wang 2018). This is why many physicians only adopt AI-enabled systems if they perceive a certain *superiority of the AI* over their own capabilities and expertise (Keeffe et al. 2005). Further, the AI still needs to deliver *explainable AI results* and insights, as physicians want to control and be able to report the results at any time (Rai 2020). However, physicians also fear *image loss* because they consult the computerized support tools, as they think society expects them to be flawless and perform their job without those tools (Shaffer et al. 2013). Physicians will regret the adoption of the cognitive agent in case of severe consequences like death (Loomes and Sugden 1982). Consequently, physicians' anticipated regret toward adopting a cognitive agent is respectively high. Furthermore, suppose the AI is perceived as too competent. In that case, physicians fear *future task dependence* in terms of future physicians relying too much on the AI and being unwilling to develop the capabilities on their own (Longoni et al. 2019). Also, physicians expect less appreciation from patients when they treat patients or fulfill tasks supported by computerized support tools (Shaffer et al. 2013). This *reduced patient esteem* is perceived as especially high when physicians devolve tasks to the support tools, acting autonomously.

Category	Construct	Definition	Related to	Examples
Enablers	Trust	The degree to which the physician is convinced of the cognitive agent concerning its reliability, functionality, helpfulness, competence, integrity, and benevolence (adapted from Komiak and Benbasat 2006).	AI, physicians' perspective	Falcone and Castelfranchi (2001), Goldszmidt and Yemini (1998), Gombolay et al. (2018), Komiak and Benbasat (2006), Rai (2020), Rzepka and Berger (2018)
	Relative time advantage	The degree to which the use of the cognitive agent is expected to be more efficient than the current task accomplishment by a physician (adapted from Moore and Benbasat 1991).	IS, potentials	Longoni et al. (2019)
	Expected ease of use	The degree to which physicians believe that using the cognitive agent would be free of effort (adapted from Davis 1989).	IS, physicians' perspective	Gombolay et al. (2018), Rzepka and Berger (2018)
	Superiority of AI	The degree to which physicians assess the expertise and capabilities they assign to the cognitive agent in performing administrative tasks as superior to their own (adapted from McLure Wasko and Faraj 2005).	AI, physicians' perspective	Keeffe et al. (2005)
	Complementary knowledge	The degree to which physicians rate the exchange and combination of knowledge with the cognitive agent as valuable on the personal or organizational level (adapted from Collins and Smith 2006).	AI, physicians' perspective	Siau and Wang (2018), Hinds et al. (2004)
	Explainable AI results	The degree to which physicians can explain and comprehend the conclusions drawn from the cognitive agent (adapted from Rai 2020).	AI, physicians' perspective	Rai (2020), Siau and Wang (2018)
Inhibitors	Image loss	The degree to which the adoption of the cognitive agent risks physicians' image or status within the healthcare facility or society (adapted from Moore and Benbasat 1991).	AI, physicians' perspective	Shaffer et al. (2013)
	Reduced patient esteem	The degree to which physicians perceive that patients would value and evaluate the tasks performed by a cognitive agent less than the tasks performed by a physician (adapted from Chen et al. 2009).	AI, patients' perspective	Shaffer et al. (2013)
	Anticipated regret	The degree to which physicians perceive that they might regret their adoption decision concerning the cognitive agent in the future (adapted from Loomes and Sugden 1982).	AI, potentials	Rai (2020)
	Future task dependence	The degree to which physicians might feel dependent on the cognitive agent to accomplish administrative tasks in the future (adapted from Jong 2007).	AI, potentials	Longoni et al. (2019), Rzepka and Berger (2018)

Table 3. Enablers and Inhibitors from Prior Research

The identified six enablers and four inhibitors simultaneously work on the intention to adopt AI (Cenfetelli and Schwarz 2011). This means that the physician perceives these enablers and inhibitors simultaneously and will have to process them simultaneously to build the intention to adopt AI. Therefore, the enablers and inhibitors are not processed separately but as a configuration of enablers and inhibitors. Thereby, enablers and inhibitors vary in their valence, meaning that they can either be present or absent in a configuration depending on individual assessment. Present enablers have the individual potential to foster, and absent enablers have the individual potential to hinder the intention to adopt AI. The potential of present inhibitors solely hinders the intention to adopt AI, so their absence has no potential to foster the intention to adopt AI (Cenfetelli and Schwarz 2011). For example, trust in the cognitive agent represents an enabler of physicians' adoption of a cognitive agent (Siau and Wang 2018). The presence of trust fosters the intention to adopt AI (Rai 2020), whereas its absence, expressing a not trustworthy cognitive agent, hinders the intention to adopt AI (Cenfetelli 2004). In contrast, physicians do not want to lose their precious image in society (Shaffer et al. 2013). The presence of an inhibitor like image loss hinders the intention to adopt AI (Shaffer et al. 2013), whereas not losing the image does not foster the adoption (Cenfetelli 2004).

3.2 Integration

The aggregation of enablers and inhibitors to a cohesive whole, thus a configuration of enablers and inhibitors, happens in the **integration** phase (Campbell et al. 2016). The reason for that lies in the ability of the human brain to recognize patterns in combined information that simplify the interpretation and assessment of the information, resulting in a decision (Pelli and Tillman 2008). Thereby, the human brain is trained to perceive the world in a holistic configurational way, recognizing sense within simultaneously perceived attributes, here the enablers and inhibitors, through cognitive structures that represent the knowledge about a decision, including the relations among them (Pelli and Tillman 2008). For example, imagine one would perceive one object with four legs and a seat and a second object with four legs, a seat, and a back. The recognition and interpretation of the former to be a stool and the latter to be a chair, so as similar, but different objects, are done quickly. However, the interpretation would not have been possible by processing and recognizing the attribute of having four legs in isolation (Campbell et al. 2016).

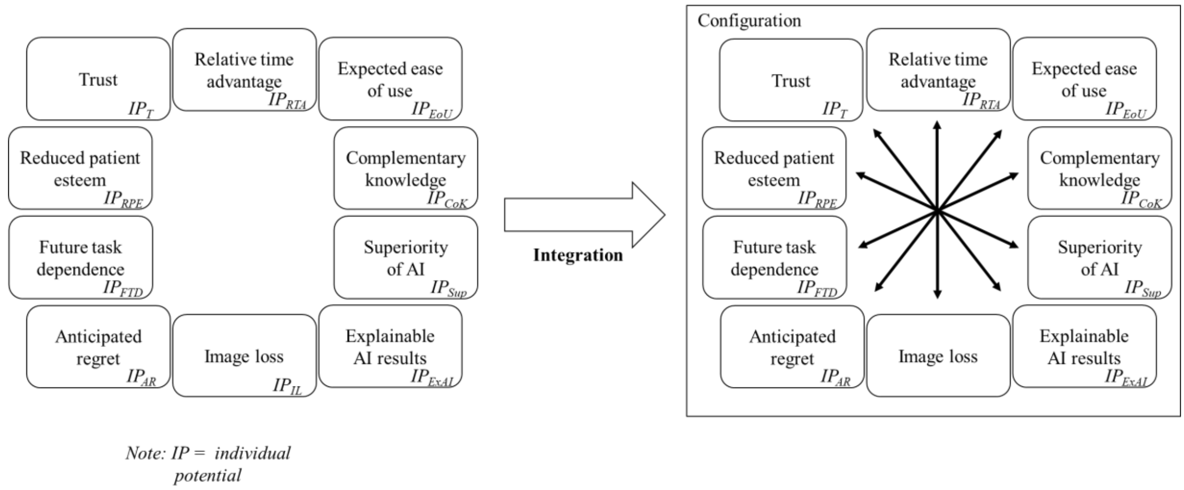


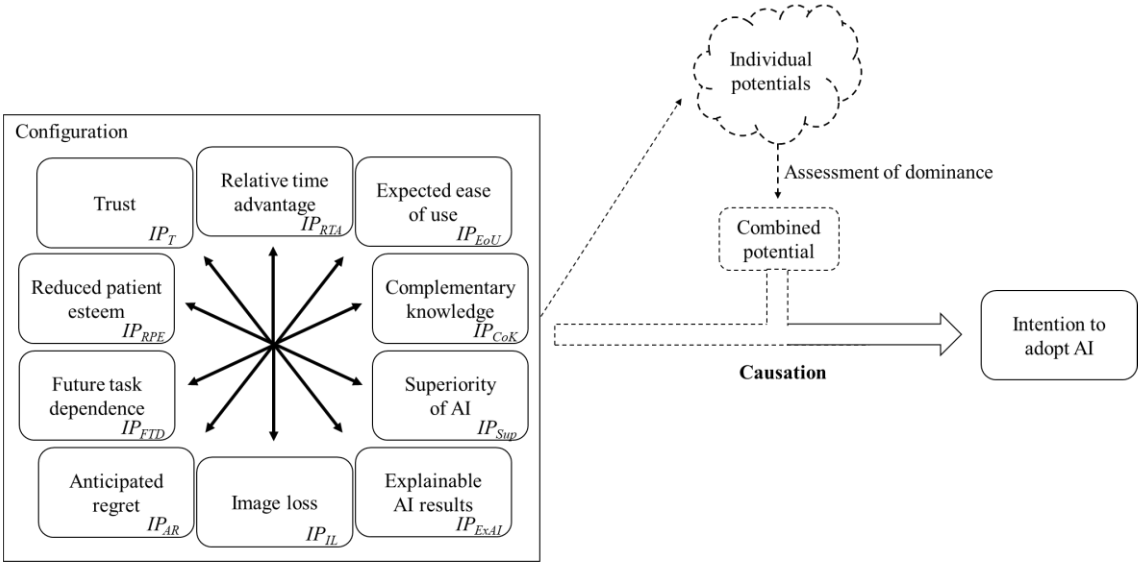
Figure 3. Integration of Relevant Enablers and Inhibitors into a Configuration

Here, physicians integrate the enablers and inhibitors they perceive about adopting a cognitive agent to a configuration of enablers and inhibitors (see Figure 3). Those configurations of enablers and inhibitors represent their current knowledge about adopting the cognitive agent, including the relevant perceptions and the attributed individual potentials influencing the intention to adopt AI. As perceptions vary between individuals (Cenfetelli and Schwarz 2011), enablers and inhibitors can vary in their valence, meaning that they can either be present or absent in a configuration, leading to differing configurations among physicians.

3.3 Causation

The intention to adopt AI, here the cognitive agent, is built within the **causation** phase by associating the configuration of enablers and inhibitors with the consequences of the actual adoption (Campbell et al. 2016). This happens in two steps: First, the physicians build the combined potential of the configuration by aggregating the individual potentials and prioritizing them, thus assessing them as dominant or subordinated. Second, the combined potential resulting from this assessment forms physicians' intention to adopt AI. Prior literature (Cenfetelli and Schwarz 2011; Ito et al. 1998) informs us that individual potentials are not just accumulated equally, but some individual potentials might be perceived as dominant in building the combined potential of the configuration. Which of the individual potentials are perceived as dominant is subject to prior experiences, biases, and preferences. For example, prior literature shows that the individual potentials attributed to present inhibitors tend to influence the assessment of the combined potential more strongly than the individual potentials attributed to present enablers (Ito et al. 1998; Maier et al. 2015; Polites and Karahanna 2012). Therefore, the literature argues that when assessed in combination, the individual potentials attributed to present inhibitors are perceived more strongly than the individual potentials of present enablers in building the combined potential of the configuration (Cenfetelli 2004) (see Figure 4).

In the context at hand, prior research has well explained the individual potential attributed to enablers and inhibitors (Cenfetelli and Schwarz 2011). Present enablers are attributed with the potential to foster the intention to adopt AI, and absent enablers with the potential to hinder the intention to adopt AI. Present inhibitors are attributed with the potential to hinder the intention to adopt AI, whereby the potential of absent inhibitors does not have an influence (Cenfetelli and Schwarz 2011). However, there is room for investigations into how physicians build the combined potential of enablers and inhibitors within a configuration, which is theoretically relevant to understand as the combined potential is actually influencing the intention to adopt AI.



Note: he three-staged processing happens within one attempt in the human brain. Dashed lines and objects represent processes that are theorized, but not included into the measurement model but examined qualitatively

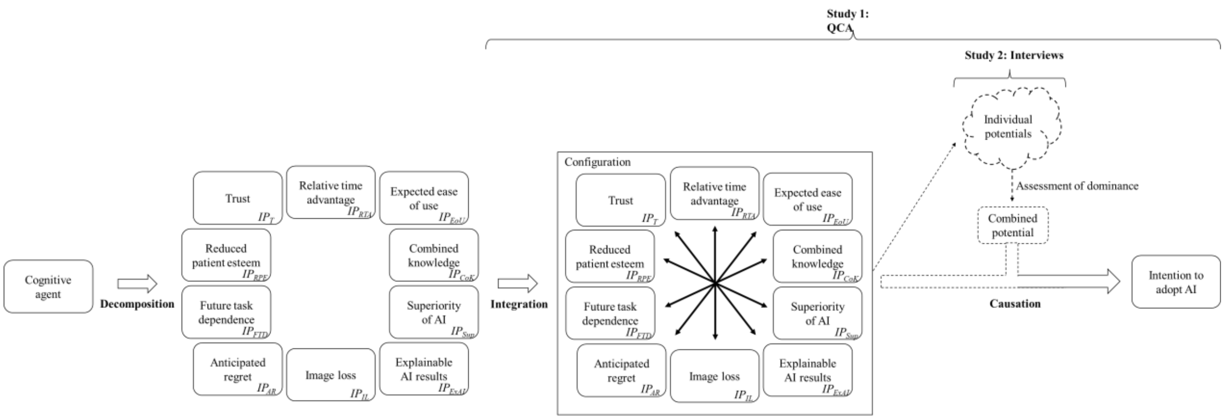
Figure 4. Building the Combined Potential of the Configurations, Influencing the Intention to adopt AI

When assessing the combined potential of the configuration as a whole, physicians simultaneously perceive the positive individual potential of present enablers for the intention to adopt AI and the negative individual potential of absent enablers and present inhibitors. Depending on prior experiences, biases, and preferences (Ito et al. 1998), the physician will have to assess which individual potentials are perceived as dominant to build the combined potential of the configuration, forming the intention to adopt AI. For example, let us consider a constellation where a physician perceives the cognitive agent as increasing efficiency and as trustworthy. Both perceptions have an individual potential to positively influence the intention to adopt AI. Simultaneously, the physician fears image loss, having the individual potential to influence the intention to adopt AI negatively. Then, the combined potential of the configuration is built, depending on which of the individual potentials are perceived as dominant over the others (see Figure 4), which has not been examined so far.

Suppose the physician perceives the increased efficiency and trust as dominant compared to an image loss. In that case, the individual potentials of the present enablers are included dominantly in building the configuration's combined potential, which will yield a high intention to adopt AI. If the physician perceives the increased efficiency and the trust as subordinated compared to an image loss, the individual potential of the present inhibitor is included dominantly in building the configuration's combined potential, yielding a low intention to adopt AI.

To investigate whether physicians would adopt a cognitive agent, ultimately realizing the assigned benefits, we need to understand the processing forming the intention to adopt AI and especially the integration and causation phase in more detail. Therefore, we need to examine which configurations of enablers and inhibitors physicians perceive and which of the attributed individual potentials they assess as dominant in building the combined potential of the configuration. Furthermore, we need to investigate why these individual potentials are perceived as dominant to provide compelling implications enabling the intention to adopt AI. Our research approach is described in more detail hereafter.

4 RESEARCH APPROACH: A MIXED-METHODS APPROACH



Note: he three-staged processing happens within one attempt in the human brain. Dashed lines and objects represent processes that are theorized, but not included into the measurement model but examined qualitatively.
IP = individual potential

Figure 5. Research Approach

We follow a mixed-methods approach (Venkatesh et al. 2013), aiming to empirically validate our theorizing of the processing forming the intention to adopt AI. Study 1 uses qualitative comparative analysis (QCA) for a configurational analysis. We use QCA because it enables us to theorize and analyze complex phenomena (Furnari et al. 2020), such as the decision to adopt a cognitive agent. QCA allows us to comprehend present and absent enablers and inhibitors as configurations and shows the combined potential built through assessing dominance regarding the individual potentials (Misangyi et al. 2017). In Study 2, we zoom into the causation phase, analyzing which individual potentials have been assessed as dominant or subordinated and why. Therefore, we complement our results with insights gained from interviews with a subset of physicians from the sample of Study 1 (see Figure 5).

Although the results of the mixed methods approach are theoretically nested, as we use the results of Study 2 to zoom into the results of Study 1 (see Figure 5), methodologically, we can only gain the results sequentially, as we need the identified configurations first to build on them in Study 2 (Venkatesh et al. 2013). So, we conduct a sequential, partially-mixed, configurational-dominant mixed methods approach with a complementary expansion purpose, as Study 2 provides expanding knowledge on the results of Study 1 (Venkatesh et al. 2013). Our multi-strand approach consists of two individual studies, one configurational Study 1 and one qualitative Study 2, based on the same worldview constrained by our theoretical model. Conducting a meta-analysis of both studies, we get a better picture of the underlying processing forming the intention to adopt AI, as demanded in prior research (Liu et al. 2017; Straatmann et al. 2018; Sussman and Siegal 2003) and additionally validate out theorizing by interviewing an external sample. We provide a validation of our mixed-methods approach in Appendix B.

4.1 Study 1: Configurational Approach Based on QCA

4.1.1 Data Collection and Sample

To collect data, we aimed to sample physicians currently working in a hospital who have not yet used a cognitive agent, as we want to examine the intention to adopt AI. Currently, the hospital plans to integrate a cognitive agent into the anamnesis-diagnosis-treatment-documentation processes, embracing all three components of AI: automation, decision support, and engagement (Davenport and Ronanki 2018). The cognitive agent automates the documentation of anamnesis[14] and treatment[15]. In the first step, the cognitive agent uses natural language processing to record what the patient or physician says and then maps the conversation into predefined standardized scales and descriptions within the electronic health record (EHR) system[16]. For example, the verbal description of pain, thus the pain severity, chronicity, and experience, must be converted into a scale value. Further, the cognitive agent provides the structured data to the physician, and, analyzing this data, the cognitive agent delivers a second

[14] Anamnesis is the process of physicians asking patients about their condition, their symptoms and medical history. For more information see https://www.ncbi.nlm.nih.gov/pubmed/26710199

[15] Treatment describes physicians' executable actions at the patient, meaning, but is not limited to, hospitalization, laboratory tests, surgery, or prescription of drugs. https://medical-dictionary.thefreedictionary.com/treatment

[16] For more information see https://www.iso.org/standard/50122.html

opinion on diagnosis and treatment possibilities. This means the cognitive agent applies the new patient data to a previously learned machine learning model trained by historic medical patient data. Based on the trained machine learning model, the cognitive agent predicts potential diseases and treatments for the new patient. Due to the cognitive agent's engagement component, the patient no longer communicates with the physician for anamnesis, but with the cognitive agent that uses the structured data to also ask for missing information or more details. The hospital's medical chief and CIO presented the implementation project to physicians in a workshop session. Also, they administered the survey, which was sent to 200 out of 350 physicians directly after the workshop, a number that we agreed on with the hospital's ethical committee. The survey contained an ID to identify the physicians for further analyses. Still, this information was exclusive to the research team, and the hospital officials could not match the participants with the survey. The survey was available for six weeks in early 2019. The response rate was 80.50 percent, as 161 out of 200 physicians filled out the survey, which is typical for medical contexts (Hulley 2007). We removed three invalid responses as the participants indicated a higher working experience than their age, and four answered two attention tests (‘Please click on ‘strongly agree’’) wrong. The final data sample consists of 154 physicians, who, on average, are 35.51 years old and have 12 years of working experience. Most physicians are male, and around three quarters work in surgery, including all surgical specialties and anesthesia. One quarter works in conservative medicine, which includes all medical specialties that are non-invasive in their treatments (see Table 4). For the fsQCA method, we describe in the next section the minimum required sample size to avoid finding random sufficient configurations for this study is 50 (Marx 2010; Marx et al. 2014). Therefore, we can say that we fulfill the sample size requirements in this study. This study relies on self-reported data, and even though the participants were unaware of the study's goal, we tested whether common method bias distorts our data. The three test results show that CMB is not an issue in this study (see Appendix F). Our role during this study was solely observatory, as we did not influence the cognitive agent's design or implementation decisions and did not influence physicians' intentions in any way.

Biological in percent		**Age in percent** Mean: 35.51 Std.: 8.92		**Years of work experience in percent** Mean: 12.61 Std.: 7.82		**Professional sector in percent**	
Male	61.69	21-30	42.86	<5	10.38	Conservative medicine	27.27
Female	38.31	31-40	34.42	5-10	21.14	Surgery	72.73
Others	0.00	41-50	16.23	11-15	21.14		
		>50	6.49	16-20	36.36		
				>20	10.38		

Note: Std. = standard deviation

Table 4. Demographics of 154 Physicians

4.1.2 Data Analysis

To analyze our data, we use the set-theoretic configurational approach (El Sawy et al. 2010; Misangyi et al. 2017) of fuzzy-set qualitative comparative analysis (fsQCA) (Ragin 2000). FsQCA is currently the dominant and most appropriate data analysis method for set-theoretic configurational approaches. It is increasingly prevalent across business and behavioral sciences and gaining attraction in IS research (e.g., Bui et al. 2019; Dawson et al. 2016; Park et al. 2020). FsQCA is an analytic method grounded in set theory and Boolean algebra (see Table 5 for an overview of the terminology and concepts) that examines the relationship between configurations of present or absent conditions and an outcome of interest (Ragin 2014). Conditions and the outcome are represented as fuzzy sets to differentiate two extreme situations of set membership (Ragin 2000). A condition (e.g., trust) can be fully-in a set, represented by the fuzzy set value of 1 (e.g., presence of trust), or can be fully-out of a set, represented by a fuzzy value of 0 (e.g., absence of trust). All values between zero and one represent a certain membership of being fully in or out of a set. For instance, a fuzzy value of 0.80 for trust indicates that trust is present, while a fuzzy value of 0.20 indicates that trust is absent.

For the data analysis, we used the QCA R package to prepare the data (Duşa 2018) and the fsQCA 3.0 software for the analysis (Ragin et al. 2016). We proceed in three steps (see Appendix C for more details). First, we calibrate the survey data into fuzzy sets. We then analyze what sufficient configurations yield a high or low intention to adopt the cognitive agent. Finally, we examine whether there are necessary conditions within sufficient configurations.

Key Term	Definition
Condition	In this study, conditions refer to the five enablers and the four inhibitors. Conditions are represented in fuzzy sets ranging from 0, indicating that a condition is completely absent, to 1, indicating that a condition is entirely present.
Configuration	In this study, a configuration refers to a specific group of conditions associated with a high or low intention to adopt AIs.
Sufficient configuration	In this study, a sufficient configuration is a configuration that exceeds a frequency threshold of three, a raw consistency threshold of 0.85, and a PRI threshold of 0.85. This means that sufficient configurations are found to consistently yield either a high or low intention to adopt AI. Multiple sufficient configurations are minimized through logical minimization. Therefore, we can say that a condition in a sufficient configuration is either present (in the results indicated with ●) or absent (in the results indicated with ⊗), or a condition can also be either present or absent, which refers to a 'don't care situation' (in the results indicated with blank space).
Necessary condition	In this study, an enabler can be necessary within configurations, yielding a high intention to adopt AI. This means that an enabler that is a necessary condition always exists in configurations yielding a high intention to adopt AI. An inhibitor can be necessary within configurations, yielding a low intention to adopt AI. This means that an inhibitor that is a necessary condition always exists in configurations yielding a low intention to adopt AI. A necessary condition needs to exceed the consistency threshold of 0.90.

Table 5.Terminology of QCA

4.1.3 Operationalization of Variables

To operationalize our variables, we consulted established literature to identify appropriate variables and adjusted the items to this study's AI and healthcare context. We measure adoption on the system level with the cognitive agent, neither on the component level treating the different AI-components of automation, decision support, and engagement, nor on the technology level treating machine learning or natural language processing. Therefore, we tried to integrate all components of the cognitive agent into our items and asked physicians to rate the 'AI,' as they were unable to differentiate between the components. All items were measured on a Likert-scale ranging from 7 ('strongly agree') to 1 ('strongly disagree'). We tested our items with medical students. For those items where we had to change the nature of the variable or where there was no prior variable to base on, we conducted a Q-sorting (see Appendix D).

Trust. Research has used many scales to measure trust (Mcknight et al. 2002). As we focus on the human-to-human-like interaction between the cognitive agent and the patients or the physician, we decided to integrate a scale to measure trust in human-to-human interaction based on benevolence, competence, and integrity (Mcknight et al. 2002). Therefore, we adapted nine of the original items to our context of the interaction with a cognitive agent. For example, we transferred the item 'I believe that LegalAdvice.com would act in my best interest' to 'I believe that the AI would act in patients' best interest.'

Relative time advantage. To measure relative time advantage, we ground on the construct of relative advantage used in the context of adaptive usage of innovative IS (Moore and Benbasat 1991). We adapted four items related to the time dimension of this construct. As the relative time advantage is vastly tied to the automation component of the cognitive agent, we primarily focused on the automation of documentation for this variable. For example, we adapted the item 'Using a PWS improves my job performance' to 'Delegating the documentation to the AI improves my job performance.'

Expected ease of use. To measure the expected ease of use, we based on items describing experienced ease of use with IS innovations (Moore and Benbasat 1991). We adapted the seven items to describe an expectation, not an experience, of effort in utilizing the cognitive agent. This adaptation is especially important, as physicians especially show a low intention to adopt AI that is not easy to use IS (Gombolay et al. 2018). For example, we adapted 'My using of a PWS requires a lot of mental effort' to 'I believe that using the AI requires a lot of mental effort.'

Complementary knowledge. The design of this variable was oriented at human knowledge combination (Collins and Smith 2006). As we wanted to stress the complementarity of the knowledge, we could not adopt the items exactly and, therefore, self-developed items using Q-sorting (see Appendix D). The items relate to the decision support component of the AI and cover the diagnosis. We tried to integrate some of the original items within our seven items. For example, we adapted 'Employees believe that by exchanging and combining ideas they can move new projects or initiatives forward more quickly than by working alone' to 'I think that the consideration of diagnosis suggestions of the AI allows faster diagnoses than without the AI.'

Superiority of AI. As we could not find any variables related to technological superiority, we self-developed three items for measuring the superiority of AI. We decided to direct this one primarily to the automation task to not conflict with the complementary knowledge variable. For Q-sorting, see Appendix D.

Explainable AI results. This variable considers examinations on how explainable AI should be designed regarding transparency in decision support and replicability of the results (Rai 2020). As, to the best of our knowledge, literature does not provide items on that, we self-developed three items concerning the decision support component of the cognitive agent with Q-sorting (see Appendix D).

Image loss. To measure this variable, we inverted the items on gaining image through IS adoption from existing literature (Moore and Benbasat 1991). As we changed the nature of the variable, we decided to validate the items with Q-sorting (see Appendix D). As the patient only engages with the cognitive agent during the documentation of anamnesis, we designed these items around the automation component of the cognitive agent. As prior research shows that individuals are less likely to be honest about themselves if the question affects social desirability (Richman et al. 1999), we framed our seven items around physicians in general rather than using ‘me.’ For example, we adapted the item ‘Because of my use of a PWS, others in my organization see me as a more valuable employee’ to ‘ Delegating the documentation to the AI, the hospital considers physicians as less valuable employees.

Anticipated regret. We base our items on a variable from regret theory, treating decision-making with uncertain consequences (Loomes and Sugden 1982). We adapted the three items to the context of cognitive agents, referring to the whole agent and treating anticipated action regret, where we regret our actions, instead of inaction regret, where we regret the lack of action. For example, we adapted the item ‘If the investment fails, I will regret having spent that money’ to ’If the AI makes a mistake, I will regret using it.’

Future task dependence. We draw on psychology research to measure future task dependence, which has examined the dependence on colleagues (Jong 2007). As we changed the nature of the variable to describe the dependence from the cognitive agent in all its activities, and we wanted to specify the dependence and not only rate the degree of dependence, we self-developed the items using Q-sorting (see Appendix D).

Reduced patient esteem. We leveraged insights from customer service (Chen et al. 2009) to measure physicians’ assumptions of patient reactions toward the cognitive agent supporting diagnosis and documentation. The original variable treats customer service evaluation in the hotel business with a scale measuring satisfaction and re-booking. We adapted four items to the contexts of patients’ evaluation of the AI and used it to capture the negative patient evaluation. For example, we adapted ‘How would you rate your overall satisfaction?’ to ‘If an AI performs the documentation and diagnosis suggestions, patients would be less satisfied with the visit.’

Intention to adopt AI. To measure the intention to adopt AI within our context, we enriched an existing variable from the field of decision aids with delegation (Komiak and Benbasat 2006). We adapted two items from ‘I am willing to let this RA assist me in deciding which product to buy’ to ‘I am willing to delegate the documentation and diagnosis suggestions to the AI.’

4.1.4 Measurement Model

To validate the measurement model, we test for indicator reliability, construct reliability, and discriminant validity (Bagozzi 1979). To test for indicator reliability, we calculated the loadings of each measurement item for the corresponding constructs. One measurement item for trust and one for image loss showed a loading below 0.707, which indicated that it explains less than 50 percent of the variance of the respective construct (Carmines and Zeller 2008) and thus has been removed. All measurement items have a loading higher than 0.707, and the measurement model fulfills the indicator reliability criterion. To test construct reliability, we calculated Cronbach’s Alpha, composite reliability (CR), and average variance extracted (AVE) for each construct (Cronbach and Meehl 1955; Fornell and Larcker 1981). Cronbach’s Alpha of each construct exceeds the threshold of 0.70, the AVE of each construct is higher than the 0.50 threshold, and the CR is higher than the 0.70 threshold (see Appendix D). This indicates that the measurement model fulfills the construct reliability criterion. We can state that discriminant validity is not an issue in the measurement model because the square root of the AVE (included on the diagonal of the bivariate correlation in Appendix D) is greater than the corresponding bivariate correlations (Fornell and Larcker 1981; Hulland 1999). We see that there are no high bivariate correlations (>0.90), and the maximum heterotrait-monotrait (HTMT) ratio is 0.83 and thus lower than the absolute HTMT0.85 threshold (Henseler et al. 2014).

4.1.5 Results

The analysis for sufficient configurations revealed three sufficient configurations yielding a high intention to adopt AI and one sufficient configuration yielding a low intention to adopt AI. We display the sufficient configurations in Figure 6.

	Combined potential yielding a high intention to adopt AI			**Combined potential yielding a low intention to adopt AI**
	C1	**C2**	**C3**	**C4**
Enablers				
Trust	★	★	★	⊗
Relative time advantage	●	●	●	⊗
Expected ease of use	●	●	●	
Complementary knowledge	★	★	★	⊗
Superiority of AI	●		●	⊗
Explainable AI results	★	★	★	⊗
Inhibitors				
Image loss	⊗	⊗		★
Anticipated regret		●	●	●
Future task dependence	●	●	●	●
Reduced patient esteem	●	●	●	●

Raw coverage	0.37	0.34	0.62	0.32
Unique coverage	0.34	0.03	0.31	0.32
Consistency	0.97	0.96	0.95	0.96
Solution coverage		0.71		0.32
Solution consistency		0.96		0.96

Note: Black circles (●) show high motivation, white crossed-out circles (⊗) show low motivation, and blank spaces ( ) indicate a 'Don't care situation.' In this case, the specific condition is irrelevant to the configuration and can either be high or low. Black stars indicate a necessary condition.

Figure 6. Graphical Presentation of the Sufficient Configurations with a Combined Potential to yield a High or Low Intention to adopt AI

The solution consistency is 0.96 for all sufficient configurations, yielding a high intention to adopt AI, and 0.96 for all sufficient configurations, yielding a low intention to adopt AI. Solution consistency indicates that all configurations are highly consistent in leading to high and low intention to use, especially as the value is well above the minimum required solution consistency level of 0.75 (Ragin 2000). The solution coverage is a measure to assess the proportion of the data set that is explained by the configurations. Thus, with a value of 0.71, the larger part of the data set can be explained by the configurations yielding a high intention to adopt AI (see Figure 6). Furthermore, each configuration has three additional measures: raw coverage, unique coverage, and consistency. If only one configuration leads to an outcome, the additional measures provide the same information as the solution coverage and consistency (Schneider and Wagemann 2012). The raw coverage refers to the extent to which this specific configuration covers the observations in the data set and ranges from 0.34 to 0.62. The unique coverage refers to the extent to which this specific configuration covers the observations, excluding the coverage of the other configurations. The unique coverage ranges from 0.03 to 0.34. Finally, the consistency indicates the specific consistency for the configuration ranging from 0.95 to 0.97.

As outlined above, we tested whether there were any necessary conditions that we then displayed graphically with a black star (Figure 6). More precisely, we found the presence of trust (consistency > 0.90, coverage 0.86), the presence of combined knowledge (consistency > 0.95, coverage 0.81), and the presence of explainable AI results (consistency > 0.94, coverage 0.81) to be a necessary condition for high intention to adopt AIs. In other words, in all configurations — even in those that do not exceed the thresholds to be a sufficient configuration — the three enablers always need to be present. This implies that the absence of those three enablers will always result in low intention to adopt AI. The test for necessary conditions also revealed one in the configuration yielding a low intention to adopt AI. We identified image loss (consistency > 0.91, coverage 0.52) as necessary and present in all configurations that show a low intention to adopt AI.

Looking at the configurations yielding a high intention to adopt AI, C1–C3 (see Figure 6), we see that the physicians simultaneously perceive (nearly) all enablers and inhibitors. As the combined potential of the configurations yields a high intention to adopt AI, we can conclude that, in total, the physicians perceive the individual potentials of present enablers as dominant over the individual potentials of present inhibitors and absent enablers. Interestingly, the image loss associated with adopting a cognitive agent is absent in two out of three configurations, meaning that those physicians deciding in favor of the adoption are not worried about image loss. In contrast, those deciding against an adoption all worry about risking their social status, as indicated by the necessary condition of C4. Looking at C4, we see furthermore that physicians cannot see the benefits of adopting a cognitive agent, which is why they perceive the enablers as absent, contributing to the negative individual potentials of the present inhibitors in building a combined yielding a low intention to adopt AI.

4.2 Study 2: Qualitative Interviews

Based on the insights from Study 1, we now understand which configurations of enablers and inhibitors resulting from the integration phase are assigned with a combined potential to yield a high or low intention to adopt AI. In the next step, we want to zoom into the causation and understand how these combined potentials are built by assessing the dominance among the individual potentials within a configuration.

4.2.1 Data Collection and Sample

For our qualitative study, we based on a nested sample from Study 1, expressing that we asked a subgroup of participants from our survey. We needed to use a nested sample, as we aim to offer in-depth insights regarding the dominance of each potential and their role in building the combined potential. We follow a non-probability expert sampling to identify physicians within the hospital whose perceptions of the present and absent enablers and inhibitors matched one of the identified configurations, using the ID in the survey. We backtracked our quantitative survey data and identified 16 physicians, four for each identified configuration (Figure 5), who shared with us which individual potentials they perceive as dominant in building the combined potential and why. For demographics, see Table 6.

We conducted the interviews onsite in the hospital two weeks after the survey had closed, so there was a temporal offset between the survey and the interviews to validate whether physicians’ answers in the survey were stable over time. We recorded them with the consent of the participants. Each interview lasted about 25 minutes. We showed the physicians ‘their’ configuration and explained its meaning regarding perceptions of the present and absent enablers and inhibitors. All of the physicians approved that the assigned configuration still represents their perceptions of enablers and inhibitors. They confirmed that the intention to adopt AI is still high or low, attesting to a stable intention formation through the theorized processing over time. Then we asked about their assessment of the individual potentials within the configuration, meaning which of them they perceive and have perceived as dominant or subordinated in building the combined potential of the configuration and why. Further, we asked them if anything would change their intention to adopt AI or if there were factors apart from the cognitive agent that influenced the dominant perception of certain individual potentials.

Biological sex in percent		**Age in percent** Mean: 35.51 Std.: 8.92		**Years of work experience in percent** Mean: 14.50 Std.: 10.56		**Professional sector in percent**	
Male	65.50	21-30	18.75	<5	18.75	Conservative medicine	27.27
Female	34.50	31-40	37.50	5-10	25.00	Operative medicine	72.73
Other	0.00	41-50	25.00	11-15	25.00		
		>50	18.75	16-20	12.50		
				>20	18.75		
Note: Std. = standard deviation							

Table 6. Demographics Study 2, Sample 1 (N=16)

For example, we identified a physician whose answers in the survey effectively converted into configuration C1 (see Figure 6), using the ID integrated into the survey, and asked the physician whether they would be willing to participate in our interview. If the physician agreed, we summarized the configuration in terms of present and absent enablers and inhibitors and asked the physician if the physician would adopt the cognitive agent in the future. As expected from C1, the answer was yes. Then, we asked which of the shown enablers and inhibitors they assessed as decisive for this decision, dominating the other enablers and inhibitors, and why. We did the same for the subordinated individual potentials. We closed by asking about what could endanger the adoption decision and if there have been factors apart from the ones that influenced the intention to adopt AI. We present the interview guideline in Appendix F.

4.2.2 Data Analysis

We analyzed the interviews regarding the specifics between the configurations regarding dominant individual potentials. We coded the results with MAXQDA 12 following the coding scheme by Myers (2019). We show an overview of this approach in Table 7.

In the first step, the *descriptive coding*, we identified all passages of the transcribed interviews dealing with the dominant and subordinated perceptions of individual potentials and why these individual potentials are perceived as dominant or subordinated. We then assigned descriptive codes to those text passages using direct quotes whenever possible. The first step revealed 18 distinct, descriptive codes used in step two.

In the second step, the *interpretive coding*, we applied interpretive coding to the 18 codes. This step aims to aggregate similar descriptive codes into more general interpretive codes. For instance, the descriptive codes ‘quality of diagnosis’ and ‘quality of documentation’ were interpretatively coded to ‘improved patient treatment quality.’ Overall, the second step revealed six interpretive codes.

In the third step, the *review of interpretive coding*, we formally reviewed the interpretive codes to ensure an objective coding procedure. For this, we tested for interrater reliability (Boyatzis 1998) of the interpretive coding, which needs to exceed a threshold of 0.70. Two research team members and two department employees who were not involved in the study rated the coding. We exceeded the threshold as only one descriptive code was assigned differently, reaching the interrater reliability of 0.94. The authors discussed the two codes and correctly coded them afterward.

In the fourth step, the categorizing *interpretive codes*, we categorized the six interpretive codes into combined potentials yielding a high or low intention to adopt AI. To assure objectivity, two members of the research team and two department employees who were not involved in the study coded the items independently, and we again calculated interrater reliability (Boyatzis 1998), which was 0.91. We present Coding examples in Appendix G.

Step	**Summary of the applied procedure**
First step: *descriptive coding*	Identification of transcribed interview passages to assign descriptive codes capturing the reasons.
Second step: *interpretive coding*	Applying interpretive coding on the descriptive codes from the first step.
Third step: *review of interpretive coding*	Ensuring objective coding through a review of the interpretive codes and calculating the interrater reliability.
Fourth step: *categorizing*	Categorizing the interpretive codes into *combined potentials, yielding a high or low intention to adopt AI*.

Table 7: Overview of the Four-Step Coding Approach (Adapted from Myers (2019))

4.2.3 Results

With these results, we show which individual potentials are perceived as dominant in building the combined potential of a configuration and why physicians perceive them as dominant. We structure the results according to a combined potential yielding a high or low intention to adopt AI. We provide an example of the interviews for each enabler or inhibitor with an individual potential that physicians perceived as dominant and the associated reason.

Category	Enabler/Inhibitor with a dominant individual potential (present or absent)	Reasons for dominant perception	Examples from the interviews
Combined potential yielding a high intention to adopt AI	Complementary knowledge (present)	Combining knowledge with the AI increases the quality of patient treatment and reduces misdiagnoses from humans and AI.	*'The cognitive agent offers a valuable second opinion that increases the quality of patient treatment as it might cover symptoms I would not have realized or are too seldom to see.'*
	Superiority of AI (present)	The superiority of AI leads to a broader acceptance of the cognitive agent in the future, reducing the lack of patient esteem and future dependency.	*'When we introduced robotic-supported surgery, many of us worried about the patient esteem and the decline of quality of surgeons when they can use the robot, making them dependent on it. But today, no one cares about that anymore, and the robot is perceived as a benefit for the treatment because of its superiority. Therefore, I think and hope that with a cognitive agent, it is the same, although I clearly see those issues.'*
	Explainable AI Results (present)	Physicians need to know what the AI is doing and which parameters the AI includes to control the documentation and diagnosis. This impedes patients' safety.	*'For me, it is most important that I understand what the cognitive agent is doing and which parameters are included in the recommendation in diagnostics or the documentation the cognitive agent made. Combining those insights, I tell the patient earlier what they might have.'*
Combined potential yielding a low intention to adopt AI	Trust (absent)	The ethical responsibility makes it impossible to risk patients' safety by adopting a system physicians do not trust.	*'If I cannot trust the cognitive agent, I would not let the results jeopardize patients' safety in treatment.'*
	Explainable AI results (absent)	If physicians cannot explain the AI results, they question their quality, as they rate their own expertise much higher than the capabilities of the AI.	*'The AI interprets the data, and I need to see the primary data or detailed explanation of the results to judge and control it against my own expertise.'*
	Image loss (present)	Physicians are not willing to risk their social status for a cognitive agent, especially if they perceive that it does not benefit them.	*'If the cognitive agent does something wrong, it is on us to take the blame, and even if the diagnoses are right, the patients might think that I cannot come to the results myself. This is dangerous, as they might lose trust in us and rely more on the internet than the doctors.'*
	Anticipated regret (present)	Physicians feel that when adopting a cognitive agent with faulty capabilities, they might regret it in the future when they jeopardize the patients' safety.	*'I would definitely regret if I trusted blindly in a faulty premature cognitive agent and put my patients at any risk.'*

Table 8. Overview of Interview Results (for Coding Examples and Guideline, see Appendix)

Leveraging the insights from the interviews, we see that physicians process the enablers and inhibitors as one configuration, where some enablers and inhibitors compensate for others and are dominant in building the combined potential. For example, the explainability of results and trust in the cognitive agent compensate for the present inhibitor of anticipated regret. This is mainly because retracing the results of the cognitive agent enables the physician to keep control, which reduces the risk of regrettable unrevealed misdiagnoses the cognitive agent could make (see Table 8). Further, physicians currently perceive that using a cognitive agent will create future task dependence and cause reduced patient esteem. Still, they rely on the development of the cognitive agent in the future and the overall technological improvement to solve these problems. This is why the individual potentials assigned to future task dependence and reduced patient esteem are perceived as subordinated in building the combined potential.

We also gain insights on preferences leading to individual potentials physicians perceive as dominant. Interestingly, physicians reported that they perceive the individual potentials of relative time advantage and expected ease of use as subordinated in building the combined potential because they affect solely the physicians' advantage of adopting the cognitive agent but not the patients' (see Table 8). The results show that with explainable AI results, superiority of the AI, and complementary knowledge, the individual potentials related to improving the treatment quality for the patient outperform those related to the reduction of efforts for the physician. Here, the physicians' fulfillment of their ethical responsibility influences individual potentials to be perceived as dominant or subordinated in building the combined potential (see Table 8). Ten out of twelve physicians said that if they were just responsible for themselves, they would have assessed the relative time advantage as dominant, profiting from the relief and the expected ease of use. However, they feel, above all, responsible for their patients. Therefore, the cognitive agent particularly needs to be a safe gain for patient care, which is why they assess the individual potentials of the superiority of the AI, complementary knowledge, and explainable AI results as dominant over the individual potentials of relative advantage and expected ease of use.

Regarding the configuration with a combined potential yielding a low intention to adopt AI (see Figure 6, C4), four out of four physicians rated the individual potentials of the absence of trust and explainable AI results and those of the presence of anticipated regret and image loss as dominant. Those four dominant individual potentials determine that the combined potential yields a low intention to adopt AI. The physicians rated their own expertise higher than the abilities of a cognitive agent and were aware of their reputation of being almost omnipotent and omniscient. Making misleading diagnoses because of the AI would harm this reputation (see

Table 8). Interestingly, the fear of image loss and anticipated regret dominated the individual potentials of the remaining inhibitors. This is because, in combination with the absence of trust and explainable AI results, physicians were not willing to risk their social status for a technology that does not bring about any guaranteed benefits and, therefore, can only degrade the competence and potency of the physicians.

4.3 Meta-Analysis of Both Studies and External Validation

Drawing upon the results from Studies 1 and 2, we integrate the gained insights into a meta-analysis to leverage the complementary insights from both studies. Further, we additionally collect data from an external sample to validate our theorizing externally.

4.3.1 Complementary Knowledge Gained from Both Studies

Prior research on the adoption of IS and AI in healthcare shows that to decide on the adoption of a cognitive agent, physicians have to integrate their own perceptions about the IS and the AI, patients' perceptions, and the potential of those perceptions to yield consequences related to the adoption (Payton et al. 2011; Shaffer et al. 2013). The perceptions about the IS thereby focus on the technological and social characteristics of the IS, whereas the perceptions about the AI are related to the AI's capability to interpret data and interact with users (Rai 2020). The identified enablers and inhibitors related to the decision to adopt a cognitive agent fall into these categories of perceptions, as they cover the physician (e.g., relative time advantage), the patient (e.g., reduced patient esteem), and consequences (e.g., future task dependence) and are either directed towards the IS (e.g., expected ease of use) or the AI (e.g., explainable AI results).

Study 1 confirms the identified enablers and inhibitors from previous research by showing that each of the identified enablers and inhibitors contributes to the decision of whether to adopt a cognitive agent. Further, the results show which specific combined present and absent enablers and inhibitors have the combined potential to yield a high or low intention to adopt AI. Thereby, the contribution of a specific enabler or inhibitor is not symmetric. For example, in configuration C2, the presence and the absence of superiority of AI contribute to a high intention to adopt AI. Also, the absence of superiority of AI simultaneously contributes to a low intention to adopt AI, which shows that the effect of a specific enabler or inhibitor can only be assessed in combination with others in the configuration, not separately. The insights of Study 2 confirm this consideration, as they show that the effect of a specific enabler or inhibitor can change in combination with others. For example, relative time advantage seen from the physicians' perspective alone is extremely important for an adoption decision. However, Study 2 shows that the effect of relative advantage is reduced in combination with perceptions of treating the patient or consequences because it is assessed as less dominant in combination with others.

Further, Study 1 and Study 2 complement each other by highlighting certain enablers and inhibitors that are especially important to the decision to adopt a cognitive agent. Study 1 identifies necessary conditions, thus those enablers and inhibitors that always exist, when forming either a high or low intention to adopt AI. Study 1 identifies trust, complementary knowledge, and explainable AI results as necessary for a high intention to adopt AI and image loss for a low intention to adopt AI. Combined with other enablers in a sufficient configuration, the necessary conditions contribute to either a high or low intention to adopt AI. Study 2, however, explains why the sufficient configurations are what they are. Looking at configuration 3, for example, we see that almost all enablers and inhibitors are present. So why is this configuration still yielding a high intention to adopt AI? This is a question of which potentials have been assessed as dominant, building the combined potential of the configuration. Here, the potentials of the present enablers were able to compensate for the potentials of the present inhibitors.

Although the combined results of both studies validate our theorizing, we cannot exclude a confirmatory bias due to the nested sample of Study 2. Therefore, we decided to additionally collect data from an external sample to confirm and validate our theorizing externally.

4.3.2 External Validation

We provide a post-hoc interview study with an external sample for external validation. We follow a non-probability sampling from the remaining physicians of the hospital, who did not receive any information about the study's goals beforehand but were aware of the hospital's plan to introduce a cognitive agent. The reason for collecting additional data outside the study is to gain additional knowledge on how physicians decide whether to adopt a cognitive agent, confirming our complementing our theorizing. Demographics can be seen in Table 9. We asked our 23 participants open questions about what they think about the cognitive agent, whether they can imagine using a cognitive agent for the anamnesis-diagnosis-treatment-documentation process and what they perceive as important regarding their decision to adopt a cognitive agent in the future. Further, we asked them how they would evaluate the cognitive agent in terms of decision making, so in other words, we followed their descriptions to validate the theorized processing resulting in adoption. All interviews were recorded transcribed and analyzed following recommendations in literature (Myers 2019). Two members of the research team and two employees of the department that were not involved in the study rated the coding, reaching interrater reliability of 0.92.

Biological sex in percent		**Age in percent** Mean: 40.56 Std.: 11.04		**Years of work experience in percent** Mean: 14.70 Std.: 10.16		**Professional sector in percent**	
Male	56.52	21-30	17.39	<5	17.39	Conservative medicine	43.47
Female	43.48	31-40	34.78	5-10	26.09	Operative medicine	56.53
Others	0.00	41-50	26.09	11-15	21.74		
		>50	21.74	16-20	13.04		
				>20	21.74		
Note: Std. = standard deviation							

Table 9. Demographics External Sample (N=23)

All 23 physicians confirmed our selection of enablers and inhibitors, stating, for example, that they need a hundred percent control over what the cognitive agent does and how it generates results, which we captured with explainable AI results. Further, they repeatedly stressed that they assume patients would not value the implementation as much as a physician would probably do and that they fear oversimplifying the medical profession, reducing patients’ trust in their physicians. They confirmed that every decision they make, not only the adoption of IS or AI, is shaped by considerations treating the physician, the patient, and the consequences of the decision. They reported that decision-making is often complex as one needs to assess all these considerations simultaneously and cannot separate their processing.

When we asked them what they thought about integrating a cognitive agent into the anamnesis-diagnosis-treatment-documentation process, they were principally open to that but also admitted that it would depict an invasive change in their work routines. As the hospital has introduced only a few IS systems, physicians have no experience with the automation of work routines. Therefore, they would first need to understand how the new system and AI integration would change their work routines and what that would mean for patients and their treatment in terms of quality and safety. 21 out of 23 physicians stated that, from their perspective, these considerations are not separable as they depend on one other. For example, they would assess reducing their workload through documentation automation as helpful, but only if the cognitive agent is reliable and not harming the patients. 20 of these 21 confirmed that it is a question of the importance of influencing factors, meaning that they must assess which perceptions are dominant and most relevant to their decision. Due to the physicians' responsibility towards their patients, they would always assess the patients’ benefits as dominant over their own. In the end, this matches the theorized processing in this study and validates our considerations externally.

5 DISCUSSION

Implementing a cognitive agent is a promising opportunity for hospitals to compensate for the rising demand in healthcare, but it also depicts an invasive change in existing processes and workflows. Having a cold start on AI due to the lack of experience with existing support systems, physicians could refuse to adopt the cognitive agent. Therefore, we provide an understanding of the processing forming the intention to adopt AI, contributing to the research streams of IS and AI adoption and AI adoption in healthcare in several ways.

5.1 Theoretical Contribution

Opening the Black Box of AI Adoption by Theorizing a Three-Stage Processing. Previous research focusing on IS adoption uses a variance perspective (e.g., Burton-Jones et al. 2015; Burton-Jones and Grange 2013) and thus provides insights into how specific, separate variables influence IS adoption to explain a high variance (e.g., in terms of R^2) of the dependent variable. In line with that research, we focus on the adoption phase of the IS use lifecycle, meaning how non-users become users (Maier et al. 2015). We further base on existing knowledge grounded in information processing research (Zadeh 1983) and complex decision-making research (Campbell et al. 2016) to better understand the processing forming the intention to adopt within the adoption phase of the IS use lifecycle. In doing so, we provide a process-oriented perspective and theorize that the processing forming the intention to adopt AI happens in three stages: decomposition, integration, and causation. We use this knowledge and first indications in IS adoption research that the intention to adopt AI results from interdependent, not separate, variables (Liu et al. 2017) to open the black box of the underlying processing. With that theoretical approach, we provide a new avenue for IS adoption research (Ajzen and Fishbein 1980; Davis 1989; Venkatesh et al. 2003), illuminating the steps undertaken when adopting an IS and specifically contributing to existent, mostly variance-oriented perspectives by offering a complementary process perspective. That said, the theoretical contribution to previous IS adoption theories is that (1) perceptions are combined and then simultaneously yield a high or low intention to adopt, (2) perceptions are assessed in their importance, meaning that some are dominant while others are subordinated, (3) this assessment of perceptions depends on the perceptions' potential in yielding consequences related to the adoption and (4) that the processing forming the intention to adopt during the adoption phase of the IS use lifecycle is not a one-in-a-whole step but can be understood in three stages.

Specifying the Asymmetric Processing of Enablers and Inhibitors. With the theorized processing, we enrich prior considerations on how the processing of enablers and inhibitors yields the intention to adopt (Cenfetelli and Schwarz 2011).

Following suggestions in prior literature that perceptions related to adoption have to be considered as interdependent variables and not as separate ones (Liu et al. 2017; Straatmann et al. 2018), our theorizing provides a detailed explanation of how the combined processing of enablers and inhibitors yields the intention to adopt AI. While prior research has so far considered the individual potentials of specific absent or present enablers and inhibitors influencing the intention to adopt (Cenfetelli and Schwarz 2011), we extend these considerations by measuring the combined potential of configurations of enablers and inhibitors in yielding a high or low intention to adopt. Thereby, we respect that enablers and inhibitors can be either present or absent within a configuration and that they can have an asymmetric influence on the intention to adopt, depending on the other enablers and inhibitors within the configuration, as elaborated in prior configurational studies (Misangyi et al. 2017). We show that whether a configuration yields a high or low intention to adopt is a question of dominance. This requires that individual potentials of enablers and inhibitors within the configuration are assessed as dominant in forming the combined potential yielding a high or low intention to adopt. The assessment of dominance can be subject to prior experiences, biases, and preferences (Ito et al. 1998; Maier et al. 2015), such as physicians' ethical responsibility towards the patient.

This theoretically contributes to the processing of enablers and inhibitors by elaborating that (1) when processed simultaneously, a specific enabler or inhibitor can contribute to a combined potential yielding a high or low adoption that is different from its individual potential influencing the adoption, (2) that the individual potentials are assessed in their dominance forming the combined potential yielding the intention to adopt, and (3) that this assessment is subject to prior experiences, biases, and preferences.

Using a Three-Stage Processing Perspective to Elaborate on AI Adoption in Healthcare. AI adoption in healthcare is highly invasive concerning AI integration, offers complexity concerning the integrated process, and yields severe consequences (see Table 2). Therefore, we use a three-stage processing perspective to elaborate on AI adoption in healthcare beyond the possibilities of existing IS adoption theories.

Our results indicate that physicians must include various information when deciding whether to adopt a new IS. This encompasses considerations regarding themselves (Keeffe et al. 2005), the patients (Shaffer et al. 2013), and the potential of those perceptions to yield consequences of the decision (Payton et al. 2011). Second, physicians simultaneously process perceptions tied to the IS, such as the expected ease of use and the relative time advantage and AI-specific perceptions addressing the capability of the cognitive agent to interact directly with physicians and patients, such as complementary knowledge, and to interpret data, such as the explainability of AI results. Third, we deliver empirical evidence that these perceptions are processed as configurations yielding either a high or low intention to adopt, which depends on assessing the enablers' and inhibitors' dominance within the configuration.

Using a three-stage processing perspective to elaborate on AI adoption in healthcare, we contribute to the research stream of AI adoption in healthcare in several ways.

With the decomposition, we contribute to the research stream of AI adoption in healthcare by categorizing and empirically validating the identified considerations related to the physicians, the patients, and the consequences in the literature and labeling them as enablers and inhibitors (e.g., Keeffe et al. 2005; Longoni et al. 2019; Shaffer et al. 2013). Further, we contribute by operationalizing AI-specific variables and their items, such as explainability of AI results, complementary knowledge, the superiority of AI, future task dependence, and image loss.

With the integration, we show the specific configurations influencing the intention to adopt AI, examining which enablers and inhibitors, in combination, yield a high or low intention to adopt AI. We identify three configurations yielding a high intention to adopt and one yielding a low intention to adopt. Further, we provide the necessary conditions involved in the adoption decision: trust, complementary knowledge, and explainable AI results for a high intention to adopt AI and image loss for a low intention to adopt AI. These enablers and inhibitors are AI-specific, treating the AI's capability to interact with users and interpret data. This illustrates the importance of AI-specific perceptions in AI adoption in healthcare.

With the causation, we contribute by showing the assessment of the dominance of individual enablers and inhibitors within a configuration yielding a high intention to adopt AI. For example, in configuration C3, nearly all enablers and inhibitors were present. So why does this configuration yield a high intention to adopt? It could also yield a low intention to adopt, especially because prior literature indicates that individuals weigh inhibitors stronger than enablers (Cenfetelli 2004), perceiving the negative more intensively than the positive (Ito et al. 1998). The intention to adopt depends on which enablers and inhibitors are assessed as dominant in influencing the adoption decision. We identified and empirically validated the dominance of AI-specific factors, such as the explainability of AI results, the superiority of AI, the dependence on AI, and the effects of AI on on-the-job feedback through image loss and reduced patient esteem, over IS-related perceptions. The underlying reason for the dominance lies in the physicians' ethical responsibility towards the patients, shaping the assessment of importance.

Leveraging these contributions helps to explain, predict, and solve problems with AI adoption, as outlined hereafter.

5.2 Practical Contributions

There are several relevant insights for healthcare providers and hospitals considering the implementation of AI-based cognitive agents in hospitals. Specifically, our results provide insights into physicians' heads in deciding whether they can imagine themselves using the cognitive agent in the future. This can be used to develop strategies to push eventual AI adoption as early as in the pre-implementation stage of the cognitive agent. Our insights suggest that hospitals need to consider physicians' perceptions and thoughts, as processing these perceptions forms the intention to adopt AI, which is decisive for the actual usage of a cognitive agent.

In terms of AI implementation, we provide several recommendations for hospitals that can also be generalized to other AI implementation projects.

Implementing a cognitive agent depicts an invasive change in existing processes and workflows that could be mitigated by integrating AI into existing support systems (Tarafdar et al. 2019). Suppose those systems do not yet exist, and the hospital is having a cold start on AI. In that case, we recommend introducing a test version of the AI with a minimum level of service such that physicians can experience the benefits of the AI integration and the capabilities of the AI.

Further, with complex processes affecting multiple users, data, and interdependent process steps, such as the anamnesis-diagnosis-treatment-documentation process, users must consider the AI adoption's effects for all stakeholder groups and the associated consequences for the process and the outcome. Therefore, we recommend a step-by-step approach when implementing the AI: One could start with automating one task at a time and then adding decision support, using labeled data to deduce patterns that support decisions through better information, and then adding the engagement component, acting as a virtual entity communicating with users. This would reduce the complexity of the adoption decision, make benefits more seamlessly demonstrable, and provide time to address worries and negative feelings toward the AI integration.

We show that physicians assess the AI-specific perceptions addressing the quality and safety of the patient treatment, such as trust, complementary knowledge, and explainable AI results, as dominant in making the adoption decision about a cognitive agent. To increase trust, we recommend hiring educated people to train the AI so that physicians see who is standing behind the system and can rely on the suggestions the AI makes. Also, we recommend establishing efforts to control and increase the explainability of AI results. To address the complementary knowledge and the superiority of AI, we recommend clearly demonstrating that the AI is a colleague, not a competitor, and that it is superior in tasks that physicians are overqualified for. This gives the opportunity to safely rely on the AI and fulfill their actual job of patient care, which converts into billable treatments for the hospital.

5.3 Limitations

This research is limited in several ways. First, theorizing the processing forming the intention to adopt AI, we base on the worldview provided by prior research on information processing (Zadeh 1983) and complex decision-making (Campbell et al. 2016). Those theories constrain our results as these worldviews only capture the cognitive processing, ignoring affective evaluations that might additionally influence the intention to adopt AI (Beaudry and Pinsonneault 2010). Second, we developed our insights from one single case of a hospital group. Although prior research has proven that one case can deliver reliable results in investigating specific phenomena (Collins and Smith 2006), different hospitals might have a different culture or different prior experiences with computerized support systems or cognitive agents that could deliver different configurations and different dominant individual potentials building the combined yielding a high or low intention to adopt AI. This does not impose a limitation on our theoretical model but on the generalizability of our results and contributions to the research stream of cognitive agents. Third, taking the survey was voluntary for the physicians, which might have biased the answers in terms of sample selection comparable to recommendations on the Internet (Hu et al. 2017), as only those who are extremely in favor of the cognitive agent or extremely against it might have taken their spare time to answer the survey. This could be one reason we do not see more variance in the configurations yielding a low intention to adopt AI. Fourth, our external validation shows that 21 of 23 physicians confirm our theorizing, depicting an approval rate of 91.30 percent. One reason we did not achieve full approval could be that the QCA approach does not provide full coverage of all existing configurations, and the remaining physicians fall into those configurations that have been left out.

5.4 Future Research

We believe there is still much to learn regarding adopting cognitive agents, which is a widely discussed topic within the discipline. With our theoretical model and the presented insights, we offer a first step towards understanding the specifics of processing the adoption decision of cognitive agents and its impact on human perceptions and tasks. Starting from here, we see some particularly promising avenues for future research, opening new paths for research on AI and organizations:

Future Research Addressing the Theorized Processing. We show the processing forming the intention to adopt AI dealing with the initial use of the cognitive agent. Future research could examine how this processing changes with continued usage or even discontinuation, integrating all phases of the IS use lifecycle as portrayed in prior research (Maier et al. 2015). Here, a continuous reevaluation of individual potentials might be necessary, as the expected individual potentials we build upon now are either confirmed or disconfirmed, which could alter the combined potential influencing use. Based on these reevaluations of individual potentials, future research needs to examine how enablers and inhibitors change over time, not just about the role of their attributed individual potentials, but also if a former enabler could turn into an inhibitor due to its evaluation. The expectation confirmation theory (Bhattacherjee 2001) or belief update theory (Bolton 1998; Hogarth and Einhorn 1992) might offer valuable considerations to complement our theorizing.

Future research should also examine the applicability of our theoretical model on negative behavioral outcomes, such as resistance. As we know from prior research, resistance is not just the opposite of use but results from different concepts and theories (Kim and Kankanhalli 2009). Examining whether the cognitive processing we provide applies to both behavioral reactions, adoption, and resistance seems worthwhile. Specifically, It will be worth considering whether this affects just an altering of the decomposition phase regarding relevant perceptions or if all three phases need to be adapted.

Another path forward would be the generalization of the three-stage processing to other adoption decisions that are highly invasive, involve complex processes, and have a high potential to yield far-reaching consequences. We suggest that our theorizing can serve to elaborate on these adoption decisions better and can be applied to other contexts.

Future Research Addressing AI Adoption. Within this research, we identified AI-specific perceptions related to the AI's capability to interact with users and interpret data. Future research could further elaborate on those perceptions, for example, by showing the non-linearity of these perceptions. Research has identified that anthropomorphic characteristics can foster acceptance, but only to a certain extent. Beyond a certain point, the anthropomorphic characteristics can be scary, referred to as the 'uncanny valley' (Burleigh et al. 2013). The same effect could apply to our AI-specific perceptions, such as the superiority of AI, as this could conflict with perceiving AI as a valuable colleague. Another valuable insight would be to talk about levels of perceptions. For example, we must ask when an explainable AI is “explainable enough” and whether we can achieve this level with computerized solutions.

Future Research Addressing AI Integration in Organizations. The healthcare context of this study shows that AI can have a valuable impact on society, but organizations are often unwilling to see the importance of technological advancement. The latest developments in global healthcare, facing a pandemic, have helped raise awareness of the need for new solutions (Yaraghi 2020). However, we must also identify means apart from extraordinary situations that motivate organizations to engage more in AI. One path could be to investigate possible interventions compensating for the inhibitors of AI adoption. For instance, this study identifies a possible image loss as part of the adoption problem. Organizational research should look into how the AI can be established as a valuable co-worker, in terms of hybrid AI and investigate how these means are perceived from an external perspective, as we see that AI can have effects outside the organization and its processes.

6 CONCLUSION

Implementing a cognitive agent is a promising opportunity for hospitals to deal with the rising demand in healthcare, but it also forces an invasive change in existing processes and workflows. Having a cold start on AI due to the lack of existing support systems, physicians could refuse to adopt the cognitive agent. This paper theorizes physicians’ processing when forming the intention to adopt AI. To do so, we base on current insights on IS adoption in healthcare, AI integration in healthcare, information processing, and complex decision-making to set up a three-stage process: decomposition, integration, and causation. In the decomposition phase, we identify enablers and inhibitors of adopting a cognitive agent, having individual potentials to influence the intention to adopt AI. In the integration phase, we examine which configurations of enablers and inhibitors have the combined potential to yield a high or low intention to adopt AI with a QCA study. Further, we zoom into the causation, explaining the building of the combined potential based on assessing individual potentials as dominant or subordinated in a configuration. We identify the dominant individual potentials and explain why physicians assess them as dominant with an interview study. With the processing when forming the intention to adopt AI, we contextualize insights from information processing and complex decision-making to the adoption context and contribute to IS and AI adoption research and research on cognitive agents. Further, we provide practical recommendations on implementing a cognitive agent successfully to realize the assigned benefits for physicians and hospitals.

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APPENDIX A: GLOSSARY

Term	Explanation	Input	Output
Intention to adopt AI	A physician's ambition to adopt a cognitive agent for administrative tasks. According to Komiak and Benbasat (2006), this is the best proxy for the actual adoption decision.		
Consequences of adoption	Goals, commitments, or values associated with the actual adoption, such as an increased performance or better patient treatment, but also possible downsides, such as image loss.		
Decomposition	Adoption decision is decomposed into relevant enablers and inhibitors that have an individual potential to foster or hinder the intention to adopt AI depending on their valence.	Decision object, here the cognitive agent	Relevant enablers and inhibitors and their individual potentials
Integration	The enablers and inhibitors are aggregated into configurations	Relevant enablers and inhibitors and their individual potentials	Configurations of enablers and inhibitors
Causation	Association of the configuration of enablers and inhibitors with consequences of the actual adoption. This happens in two steps: First, the physicians build the combined potential of the configuration by aggregating the individual potentials and assessing them as dominant or subordinated. Second, the combined potential forms physicians' intention to adopt AI.	Configuration of enablers and inhibitors	High or low intention to adopt AI
Individual potential	Attributed to each enabler or inhibitor, depending on their valence. *Present enablers* have the individual potential to foster the intention to adopt AI, and *absent enablers* have the potential to hinder the intention to adopt AI. *Present inhibitors* have the potential to hinder the intention to adopt AI, whereby the potential of *absent inhibitors* does not have an influence.		
Combined potential	Physicians build the combined potential of the configuration by aggregating the individual potentials and assessing them as dominant or subordinated. The combined potential yields either a high or a low intention to adopt AI.		

Table 10. Glossary of Key Terms

APPENDIX B: MIXED METHODS APPROACH

Table 11 shows how we followed established guidelines (Venkatesh et al. 2013; Venkatesh et al. 2016).

Mixed methods approach and guidelines utilized			
Purpose and Design	**Characteristics**	**Study**	**Additional comments**
Purpose	Complementary, expansion	Study 1 and Study 2	The qualitative study expands the results from the configurational study and gives complementary insights into the building of the combined potential influencing the intention to adopt AI.
Design	Sequential, configurational-dominant, multi-strand, paradigmatic perspective of critical realism, configurational study followed by qualitative study	Study 1 and Study 2	The interviews have a very specific purpose of examining dominant and subordinated individual potentials, building the combined potential. These insights are necessary to validate our theorizing and deepen the insights of the causation phase.
Sampling strategy	Physicians not having a user experience with a cognitive agent for documentation and diagnostics, nested samples, non-probability sampling, gathered within the case of a hospital group about to introduce a cognitive agent for documentation and diagnostics	Study 1	Survey with 161 physicians from different departments delivered three configurations yielding a high intention to adopt AI and one yielding a low intention to adopt AI.
		Study 2	Interviews with 16 of the 161 physicians from Study 1, four at a time matching each of the four configurations, zoom into the causation happening in the physicians' brains. Additionally, we interviewed an external sample of 23 physicians to validate our theorizing.
Quality aspect	**Quality criteria**	**Study**	**Application of existing guidelines**
Design quality	Design suitability/ appropriateness	Study 1 and Study 2	Drawing from our theoretical model explaining physicians' intention to adopt AI, we set up our study following the model's needs. We concluded that a pure qualitative or configurational approach could not deliver the needed insights into the phenomenon. Therefore, we chose to unite both paradigmatic strands by applying two studies and adding insights.
	Design adequacy	Study 1	We gathered data from a hospital group that is currently implementing a cognitive agent integrating automation and decision-support tasks. The measurement items are either based on previous research or validated with Q-sorting.
		Study 2	For the internal sample, we only asked physicians who matched the configurations and could get further insights into how the combined potential is built. Our sample was appropriate and big enough, with sixteen passing the threshold of six to ten(Collins and Smith 2006). For the second sample, we interviewed 23 external physicians. The physicians were aware of the

			study and the goals we are pursuing. While conducting the interviews, we were sensitive to flexibility, nondirection, specificity, and range principles.
	Analytical adequacy	Study 1	The overall validity and reliability of the measurement model are granted, and there is no evidence for common method bias. The sample size is large enough for our configurational approach, which is oriented on established guidelines for fsQCA (Marx 2006). The results of the configurational approach are robust to changes in the used thresholds and the applied calibration process.
		Study 2	We recorded and transcribed the interviews and coded them following recommendations (Myers 2019). We analyzed iteratively with two co-authors and constantly compared our results until we reached theoretical saturation (Sarker et al. 2018). We had interrater reliability of 91 percent, meaning that we got consent between the two co-authors concerning the reliability and plausibility of the results.
Legitimation	**Quality criteria**	**Additional comments**	
Explanation quality	Configurational inferences from Study 1	The degree to which interpretations from the quantitative analysis closely follow the relevant findings, are consistent with theory and the state of knowledge in the field, and are generalizable.	
	Qualitative inferences from Study 2	The gained insights were plausible, and their relevance for practice was assessed as high by the experts. We double-checked the interpretation of the results with the experts to ensure the inferential validity. The qualitative inferences fulfilled the purpose of the qualitative study in examining the assessment of combined potentials and validating our theorizing.	
	Meta-inferences integrating inferences from Study 1 and Study 2	*Integrative efficacy:* We integrated both types of inferences to formulate our propositions that originated from the meta-inferences *Inference transferability*: Our propositions are transferable to other contexts implementing AI as we describe the necessary conditions for enablers and inhibitors related to this field. Whereas image loss seems to be a contextual factor, on a broader level, we can conclude, similar to prior insights on job satisfaction (Hackman and Oldham 1980), that when AI impacts the feedback from the job, it could risk adoption because of reduced job satisfaction. *Inferential correspondence*: The mixed methods approach empirically tested our theorizing of cognitive processing to build physicians' intention to adopt AI. We needed to find an appropriate design that covers all phases of that process. Therefore, the mixed methods approach perfectly fits our purposes, and we could validate our theorizing by integrating both inferences into meta-inferences.	

Table 11. Design and Validation of the Mixed Methods Approach (Adapted from Sarker et al. (2018; Venkatesh et al.))

APPENDIX C: QCA ANALYSIS

To analyze the collected data, we first need to convert the data into fuzzy sets. We follow recommendations for calibrating survey data measured on a 7-Likert scale into fuzzy sets (Fiss 2011; Liu et al. 2017; Misangyi et al. 2017). We use direct calibration to calibrate the mean values of each construct into fuzzy sets. For this, we define three anchors. The minimum value of the 7-Likert scale (here: 1 = 'strongly disagree') is defined as the minimum fuzzy set membership (here: 0), the median value of the Likert-scale (here: 4 = 'neither agree nor disagree') is set the fuzzy set membership of 0.5, and the maximum value of the Likert-scale (here: 7 = 'strongly agree') is set to the maximum fuzzy set membership (here: 1). All values in between the three anchors are calibrated based on a log-odds transformation (Ragin 2007, 2008a). The direct calibration results in fuzzy values for all enablers and inhibitors and the intention to adopt AI. For instance, a fuzzy set membership of 1 for trust reflects a full fuzzy set membership and refers to the presence of the enabler. Conversely, a fuzzy set membership of 0 reflects a full non-membership and refers to the absence of an enabler.

With the constructs represented as fuzzy sets, we conduct the analysis for sufficient configurations of present and absent enablers that either yield a high or low intention to adopt AI. We first analyze sufficient configurations yielding a high intention to adopt AI. For this, we construct the truth table, which summarizes all configurations of the enabler and inhibitors that exist in the data set and displays the frequency of how often a specific configuration exists. For each configuration, we calculated the raw consistency as well as the proportional reduction in inconsistency (PRI) (Schneider and Wagemann 2012). Here, raw consistency refers to the degree to which the observations sharing a given configuration agree on yielding a high intention to adopt AI (Ragin 2006). The PRI (Schneider and Wagemann 2012) is a measure that indicates the degree to which observations sharing a given configuration yield a high or low intention to adopt AI consistently. Based on the constructed truth table, we reduce the existing configurations to only sufficient configurations. For this, we apply three thresholds, which are recommended in QCA literature and commonly used in IS research. We apply a raw consistency threshold of 0.85 (Koo et al. 2019; Lee et al. 2019; Ragin 2008b), a PRI threshold of 0.85 (Ragin 2008b) as well as a frequency threshold of three (Park et al. 2017), which is recommended for the sample size (Campbell et al. 2016; Maggetti and Levi-Faur 2013). This means that only configurations that exist at least three times in the data set and exceed the raw and PRI consistency threshold are considered sufficient. The Quine-McCluskey algorithm logically minimizes those sufficient configurations (Ragin 2006) to reveal more parsimonious ones. The procedure of constructing the truth table and reducing it with raw consistency, PRI, and frequency threshold is repeated for testing sufficient configurations that yield a low intention to adopt AI. The set-theoretic approach furthermore allows examining whether there exist any necessary conditions within the final sufficient configurations. A necessary condition always exists when the outcome of interest also exists (Ragin 2014). In this study, a necessary condition is either an enabler that always exists in configurations that yield a high intention to adopt AI or an inhibitor that always exists in a configuration that yields a low intention to adopt AI. From a methodological point of view, we can test the necessary conditions based on a consistency threshold. A condition is seen as necessary if this condition exceeds the consistency threshold of 0.90, which again assesses the degree to which observations agree in displaying the condition as necessary (Schneider and Wagemann 2012).

APPENDIX D: MEASUREMENT ITEMS AND Q-SORTING

Previous IS research does not provide some AI-specific measurement items for the constructs in our study, or adapting existing measurement items to the context of AI brings rather major changes in the nature of the measurement items. Therefore, we proceeded in three steps. First, we developed an initial pool of measurement items for 1) combined knowledge, 2) superiority of AI, 3) explainable AI results, 4) image loss, and 5) future task dependence on AI. The development of the initial pool of measurement items for combined knowledge was guided by similar items in the context of knowledge exchange and knowledge combination in the human-to-human context (Collins and Smith 2006). The initial pool of measurement items for the superiority of AI is deducted from the documentation task the cognitive agent executes. The measurement items for image gain inspire the initial set of measurement items for image loss through IS adoption (Moore and Benbasat 1991). Finally, the items for future task dependence are inspired by related items in the context of resource dependency (Chen et al. 2009). Second, after creating an initial set of measurement items for the four constructs, we discussed the items within our research team and with four physicians who work in the respective hospitals where the cognitive agent is going to be implemented. We used the feedback to slightly adjust the items. Third, we follow recommendations for item development (Landis and Koch 1977; Nahm et al. 2002) and apply a Q-sorting approach to assess the content validity of the measurement items, which refers to the extent to which an item represents a certain construct. Using Q-sorting is a common approach in IS research to validate the validity of measurement items (MacKenzie et al. 2011; Menor and Roth 2007). We recruited 68 medical students to sort the measurement items, which were presented in a random order to one of the four constructs. Alternatively, the participants could choose to indicate that the item does not fit any of the four constructs. In line with previous research (Landis and Koch 1977; Nahm et al. 2002), we calculated the hit rate, which indicates the extent to which an item was assigned to the correct construct. For each measurement item and rejected items with a hit rate smaller than 61 percent (see Table 12).

Construct	Measurement item	Hit rate	Others	No assignment
Complementary knowledge (CoK)	CoK1	87	1	12
	CoK2	84	0	16
	CoK3	82	0	18
	CoK4	82	1	17
	CoK5	81	2	17
	CoK6	72	3	25
	CoK7	65	5	30
Superiority of AI (Sup)	Sup1	71	4	25
	Sup2	77	1	22
	Sup3	74	3	23
	Sup4	48	7	45
Explainable AI results (ExAI)	ExAI1	77	5	18
	ExAI2	76	6	18
	ExAI3	74	0	26
	ExAI4	60	6	34
	ExAI5	51	20	29
Image loss (IL)	IL1	87	1	12
	IL2	86	3	12
	IL3	81	2	17
	IL4	75	4	21
	IL5	74	1	25
	IL6	71	0	29
	IL7	68	4	28
Future task dependence (FTD)	FDT1	81	1	18
	FDT2	78	0	22
	FDT3	77	0	23
	FDT4	77	1	22
Note: Only measurement items with a hit rate higher than 50 percent are displayed. Measurement items that have failed the hit rate threshold are colored red.				

Table 12. Results of the Q-Sorting Approach

Category	Construct	Items	Loading
Enablers	**Trust** based on Mcknight et al. (2002)	I believe that the AI ...	
		... is truthful in its dealings with me.	0.887
		... is honest.	0.815
		... keeps its commitments.	0.891
		... is competent and effective in documentation and diagnosis suggestions.	0.888
		... performs its role of documentation and diagnoses suggestions very well.	0.878
		... is a capable and proficient tool.	0.746
		... acts in patients' best interests.	<0.707
		... does its best to help the patients.	0.956
		... is interested in the patients' well-being.	0.920
	Relative time advantage based on Moore and Benbasat (1991)	Delegating the documentation to the AI…	
		…enables me to accomplish the documentation and diagnosis more quickly.	0.871
		… makes it easier to do my job.	0.749
		…improves my job performance.	0.778
		… increases my productivity.	0.795
	Expected ease of use based on Moore and Benbasat (1991)	I expect that…	
		… using the AI will be cumbersome.	0.780
		… using the AI will require a lot of mental effort.	0.904
		… using the AI will be often frustrating.	0.804
		… my interaction with the AI will be clear and understandable.	0.896
		… it will be easy to get the AI to do what I want it to do.	0.878
		… using the AI will be easy.	0.718
		… learning to use the AI will be easy for me.	0.806
	Complementary knowledge self-developed; guided by Collins and Smith 2006	I see advantages in exchanging and combining diagnostic suggestions with AI.	0.797
		I think that the consideration of the diagnostic suggestions of the AI allows faster diagnoses than without the AI.	0.801
		I can learn from exchanging diagnostic suggestions with the AI.	0.846
		I can benefit from the exchange of diagnostic suggestions with the AI	0.792
		I can gain insights into other disciplines by exchanging diagnostic suggestions with the AI.	0.837
		The AI can provide cross-disciplinary knowledge.	0.721
		The AI is a valuable enhancement to existing knowledge in the hospital.	0.824
	Superiority of AI self-developed	I think that...	
		...the AI provides more accurate documentation than I do.	0.847
		...over the time collects more experience with documentation than I do	0.836
		...the AI provides more complete documentation than I do.	0.799
	Explainable AI results self-developed; guided by Rai 2020	I think that…	
		… I am able to understand the diagnosis suggestions made by the AI.	0.904
		… I think the diagnosis suggestions made by the AI are explainable to me.	0.895
		… I am able to control the diagnoses made by the AI.	0.822
Inhibitors	**Image loss** self-developed guided by Moore and Benbasat (1991)	Delegating the documentation to the AI…	
		...is damaging the reputation of the physicians in the hospital.	< 0.707
		... the hospital considers physicians as less valuable employees.	0.753
		... reduces the esteem of physicians in society.	0.894
		... threatens the social status of the physician profession.	0.886
		... endangers the image of the physician in society.	0.900
		... reduces the importance of the physician's profession.	0.895
		... over-simplifies the physician's profession in society.	0.940
	Anticipated regret based on	If the AI makes a mistake, I will regret having used it.	0.942
		If the AI makes a misdiagnosis, I will regret having used it.	0.924
			0.828

	Loomes and Sugden (1982)	If using the AI results in a treatment error, I will regret having used it.	
	Future task dependence self-developed; guided by Jong 2007	I am afraid that by using AI, … physicians will be dependent on AI for diagnosis in the future. … physicians will not be able to perform diagnoses without AI in the future adequately. … young physicians will be less willing to train documentation and therefore will be dependent on the AI. … young physicians will be less willing to train diagnoses and thus be dependent on the AI.	 0.894 0.909 0.802 0.883
	Reduced patient esteem adapted from Chen et al. 2009	If the documentation and diagnosis suggestions are performed by an AI… … patients would be less likely to come again. … patients would be less likely to recommend our hospital. … patients would value the visit less. … patients would be less satisfied with the visit.	 0.916 0.897 0.862 0.883
Outcome	**Intention to adopt AI** based on Komiak and Benbasat 2006	I am willing to delegate documentation and diagnosis suggestions to the AI. I am willing to let this AI do documentation and diagnosis suggestions on my behalf.	0.943 0.944

Table 13. Measurement Items and Loadings

APPENDIX E: DESCRIPTIVE STATISTICS

		M.	Std.	a	CR	AVE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Trust	4.69	1.02	0.89	0.92	0.64	0.80										
(2)	Relative time advantage	4.88	1.39	0.73	0.81	0.60	0.44	0.77									
(3)	Expected ease of use	4.76	1.24	0.79	0.76	0.63	0.56	0.31	0.79								
(4)	Complementary knowledge	5.10	1.19	0.87	0.91	0.71	0.66	0.59	0.37	0.84							
(5)	Superiority of AI results	4.68	1.26	0.87	0.92	0.79	0.50	0.61	0.24	0.56	0.89						
(6)	Explainable AI results	5.11	1.24	0.85	0.91	0.77	0.47	0.74	0.46	0.59	0.48	0.87					
(7)	Image loss	4.45	1.53	0.95	0.96	0.82	-0.07	-0.07	-0.11	-0.21	0.09	-0.15	0.90				
(8)	Anticipated regret	5.24	1.35	0.90	0.93	0.81	0.09	0.02	0.04	0.09	-0.01	0.06	0.24	0.90			
(9)	Future task dependence	5.25	0.97	0.90	0.93	0.76	0.41	0.28	0.34	0.43	0.45	0.27	-0.04	0.19	0.87		
(10)	Reduced patient esteem	5.25	1.04	0.91	0.94	0.79	0.32	0.33	0.46	0.41	0.13	0.42	-0.08	0.24	0.42	0.89	
(11)	Intention to adopt as a delegated agent	4.64	1.65	0.88	0.94	0.89	0.63	0.49	0.58	0.60	0.44	0.58	-0.40	0.09	0.38	0.32	0.94

Note: All items are measured on a 7-point Likert scale from Strongly Disagree (1) to Strongly Agree (7); M. = mean; Std. = standard deviation, a= Cronbach's alpha; CR = composite reliability; AVE = average variance extracted; the square root of the AVE is displayed on the diagonal of the bivariate correlations

Table 14. Descriptive Statistics and Bivariate Correlations

APPENDIX F: COMMON METHOD BIAS

To test whether common method bias (CMB) distorts our results, we conducted three tests to assess whether CMB is an issue in this study. First, we conducted Harman's single-factor test, which assesses how much of the variance is explained by one single factor. The result of this test shows that 42 percent of the variance is explained by one factor and thus is below the recommended 50 percent. Second, we examined the bivariate correlation matrix as recommended by Pavlou (2003). The correlation matrix shows no extremely high correlations ($r > 0.9$), indicating that CMB is not an issue. Third, we applied a CMB test with the help of PLS, as proposed by Williams et al. (2003). The test requires building a PLS model with a CMB factor and transforming all other factors into single-item constructs. With this setting, we can compare the R^2 of the PLS model with and without a CMB factor, whereby a small difference is a good indicator that CMB is not an issue in the study. The result of this test shows that the CMB factor explains an additional R^2 of 0.009, which indicates that CMB is not an issue in this study (Liang et al. 2007; Williams et al. 2003). Based on three different tests, we can say that CMB is not an issue in this study.

APPENDIX G: INTERVIEW GUIDELINE

We used this semi-structured interview guideline for the 16 interviews with physicians matching the configurations in Study 2.

0 Summary of configuration and combined potential
0.1 We analyzed your answers in the survey. Summarized, you perceived it that way. Do you still agree with those perceptions? 0.2 would you decide to use the cognitive agent in the future?
1 Individual potentials perceived as dominant in building the combined potential
1.1 What was most important to you when deciding to use the cognitive agent in the future? 1.2 Are there factors that you cannot miss in your decision? 1.3 Which of the factors were decisive for your decision? 1.4 Why do you perceive these factors as more important?
2 Individual potentials perceived as subordinated in building the combined potential
2.1 What was not so important to you when deciding to use the cognitive agent in the future? 1.2 Are their factors that are compensated by others? 1.3 Which factors were nice to have but did not directly cause the decision? 1.4 Why do you perceive these factors as less important?
3 Altering assessments
3.1 What would be needed to change your mind about the adoption decision? 3.2 Is there anything besides the cognitive agent that lets you assess these factors?

Table 15. Interview Guideline

APPENDIX H: CODING SCHEME

Our coding approach uses the interpretive/descriptive coding approach presented by (Myers 2019). Table 16 shows the results of the four-step approach.

Data examples	Descriptive coding	Interpretive coding (reason)	Category
'I need to be able to report at any time.'	Understanding the AI results gives me control	Improved patient treatment safety	Combined potential yielding a high intention to adopt AI
'In my opinion, the generation of results by the cognitive agent needs to be traceable and visible to assess these in terms of what has been included.'	The included parameters need to be visible.		
'Comparing results with a cognitive agent, I can tell my patients earlier what they have.'	Timeliness of diagnoses	Improved patient treatment quality	Combined potential yielding a high intention to adopt AI
'The cognitive agent might document things that I forgot to ask or remind me to do so.'	Data completeness		
'The cognitive agent has the power to detect also seldom diseases.'	Quality of diagnosis		
'The cognitive agent provides structured and comparable documentation.'	Quality of documentation		
'Patients would not be willing to see a doctor that does not show respect to document the data himself.'	Reduced social support	Risk of social status	Combined potential yielding a high intention to adopt AI
'If the cognitive agent makes misdiagnoses, the physicians adopt. People will lose their trust in doctors.'	Lost trust in physician		
'Patients might think that I am not able to do the documentation or diagnosis alone.'	Loss of expert status		

Table 16. An Example of the Coding Procedure (Adapted from Myers (2019))

Paper IX

Addressing User Resistance Would Have Prevented a Healthcare AI Project Failure

Lea Reis
University of Bamberg

Christian Maier
University of Bamberg

Jens Mattke
University of Bamberg

Marcus Creutzenberg
Department of Anesthesiology, University Hospital Regensburg

Tim Weitzel
University of Bamberg

Reis, Lea; Maier, Christian; Mattke, Jens; Creutzenberg, Marcus and Weitzel, Tim (2020): Addressing User Resistance Would Have Prevented a Healthcare AI Project Failure, *In: MIS Quarterly Executive (19:4), Article 8*
https://aisel.aisnet.org/misqe/vol19/iss4/8

https://doi.org/10.17705/2msqe.00038

Chapter 3: Mixed-Methods in IS Research

Paper X

Mixed-Methods in Information Systems Research:

Status Quo, Core Concepts, and Future Research Implications

Lea Reis
University of Bamberg

Christian Maier
University of Bamberg

Tim Weitzel
University of Bamberg

Reis, Lea; Maier, Christian and Weitzel, Tim (2022): Mixed-Methods in Information Systems Research: Status Quo, Core Concepts, and Future Research Implications, *In: Communications of the Association for Information Systems, 51*

https://doi.org/10.17705/1CAIS.05106

Paper XI

Bitcoin investment:

A Mixed Methods Study of Investment Motivations

Jens Mattke
University of Bamberg

Christian Maier
University of Bamberg

Lea Reis
University of Bamberg

Tim Weitzel
University of Bamberg

Mattke, Jens; Maier, Christian; Reis, Lea and Weitzel, Tim (2021): Bitcoin investment: A mixed methods study of investment motivations, *In: European Journal of Information Systems, 30:3, 261-285*
https://doi.org/10.1080/0960085X.2020.1787109

Paper XII

Challenge and Hindrance IS Use Stressors and Appraisals:

Explaining Contrarian Associations in Post-Acceptance IS Use Behavior

Christian Maier
University of Bamberg

Sven Laumer
FAU Erlangen-Nürnberg

Monideepa Tarafdar
University of Massachusetts Amherst

Jens Mattke
University of Bamberg

Lea Reis
University of Bamberg

Tim Weitzel
University of Bamberg

Maier, Christian; Laumer, Sven; Tarafdar, Monideepa; Mattke, Jens; Reis, Lea and Weitzel, Tim (2021): Challenge and Hindrance IS Use Stressors and Appraisals: Explaining Contrarian Associations in Post-Acceptance IS Use Behavior, *In: Journal of the Association for Information Systems, 22(6), 1590-1624.*
https://doi.org/10.17705/1jais.00709

Appendix

PUBLICATIONS

Peer-Reviewed Journal Articles

Reis, L., Maier, C., Pflügner, K., and Weitzel, T. (2023)
Unintended consequences of technostress mitigation: An employee perspective on the effectiveness of mitigation measures
Forthcoming in: The DATA BASE for Advances in Information Systems (VHB-JOURQUAL 3 Rating: B)

Reis, L., Maier, C., and Weitzel, T. (2022)
Mixed-Methods in Information Systems Research: Status Quo, Core Concepts, and Future Research Implications
Communications of the Association for Information Systems (CAIS) (51:1), https://doi.org/10.17705/1CAIS.05106, (VHB-JOURQUAL 3 Rating: C)

Asbjørn , F., Araujo, T., Lai-Chong Law, E., Bae Brandtzaeg, P., Papadopoulos, S., Reis, L., Baez, M., Laban, G., McAllister, P., Ischen, C., Wald, R., Catania, F., Meyer von Wolff, R., Hobert, S., and Luger, E. (2021)
Future directions for chatbot research: an interdisciplinary research agenda
Computing (103:1), p. 2915–2942, https://doi.org/10.1007/s00607-021-01016-7

Mattke, J., Maier, C., Reis, L., and Weitzel, T. (2021)
In-app advertising: a two-step qualitative comparative analysis to explain clicking behavior
European Journal of Marketing (55:8), p.2146-2173, https://doi.org/10.1108/EJM-03-2020-0210 (VHB-JOURQUAL 3 Rating: C)

Maier, C., Laumer, S., Tarafdar, M., Mattke, J., Reis, L., and Weitzel, T. (2021)
Challenge and hindrance IS use stressors and appraisals: Explaining contrarian associations in post-acceptance IS use behavior
Journal of the Association for Information Systems (JAIS) (22:6), p.1590-1624, http://dx.doi.org/10.17705/1jais.00709 (VHB-JOURQUAL 3 Rating: A)

Reis, L., Maier, C., Mattke, J., Creutzenberg, M., and Weitzel, T. (2020)
Addressing User Resistance Would Have Prevented a Healthcare AI Project Failure
MIS Quarterly Executive (19:4), p. 279-296, http://dx.doi.org/10.17705/2msqe.00038 (VHB-JOURQUAL 3 Rating: B)

Mattke, J., Maier, C., Reis, L., and Weitzel, T. (2020)
Herd behavior in social media: The role of Facebook likes, strength of ties, and expertise
Information & Management (57:8), 103370, https://doi.org/10.1016/j.im.2020.103370 (VHB-JOURQUAL 3 Rating: B)

Mattke, J., Maier, C., Reis, L., and Weitzel, T. (2020)
Bitcoin investment: a mixed methods study of investment motivations
European Journal of Information Systems (EJIS) (30:3), p. 261-285, https://doi.org/10.1080/0960085X.2020.1787109 (VHB-JOURQUAL 3 Rating: A)

Peer-Reviewed Conference Articles

Reis, L. (2022)
Information Overload and Presented Lifestyle in Social Media: A Stress-Perspective on the Effects on Mental Health
Proceedings of the 22nd ACM SIGMIS Conference on Computers and People Research, Atlanta (GA), United States

Reis, L. and Maier, C. (2022)
Artificial Intelligence in Mental Health: A Qualitative Expert Study on Realistic Application Scenarios and Future Directions
Proceedings of the 22nd ACM SIGMIS Conference on Computers and People Research, Atlanta (GA), United States

Reis, L., Maier, C., and Weitzel, T. (2022)
Chatbots in Marketing: An In-Deep Case Study Capturing Future Perspectives of AI in Advertising
Proceedings of the 22nd ACM SIGMIS Conference on Computers and People Research, Atlanta (GA), United States

Meier, M., Maier, C., Reis, L., and Weitzel, T. (2021)
Amazon Prime Video Yesterday, Netflix Today: Explaining Subscribers' Switching Behavior from a Retrospective
Proceedings of the 29th European Conference on Information Systems (ECIS), Marrakesch, Marokko (VHB-JOURQUAL 3 Rating: B)
Claudio Ciborra Award Nomine

Mattke, J., Maier, C., and Reis, L. (2020)
Security Token Offerings: A Risk as Feelings Theoretic Perspective on Investment
Proceedings of the 41th International Conference on Information Systems (ICIS), Hyderabad, India (VHB-JOURQUAL 3 Rating: A)
Research in Progress

Mattke, J., Maier, C., and Reis, L. (2020)
Is Cryptocurrency Money? Three Empirical Studies Analyzing Medium of Exchange, Store of Value and Unit of Account
Proceedings of the ACM SIGMIS Conference on Computers and People Research, Nuremberg, Germany

Reis, L., Maier, C., Mattke, J., and Weitzel, T. (2020)
Chatbots in Healthcare: Status Quo, Application Scenarios for Physicians and Patients and Future Directions
Proceedings of the 28th European Conference on Information Systems (ECIS), Marrakesh, Morocco (VHB-JOURQUAL 3 Rating: B)

Pflügner, K., Reis, L., Maier, C., and Weitzel, T. (2020)
Communication Measures to Reduce Techno-Invasion and Techno-Overload: A Qualitative Study Uncovering Positive and Adverse Effects
Proceedings of the 20th ACM SIGMIS Conference on Computers and People Research, Nuremberg, Germany
Best Paper Award

Reis, L., Mattke, J., Maier, C., and Weitzel, T. (2020)
Conversational Agents in Healthcare: Using QCA to Explain Patients' Resistance to Chatbots for Medication
Proceedings of the Conversations 2020: 3rd International Workshop on Chatbot Research and Design, Amsterdam, Netherlands

Müller, L. (2019)
Enabling Digital Commerce: Advertising and the Influence of User Behavior
Proceedings of the 25th Americas Conference on Information Systems (AMCIS), Cancun, México (VHB-JOURQUAL 3 Rating: D)

Müller, L., Mattke, J., and Weitzel, T. (2019)
Not Talking to Robo-Doc: A QCA Study Examining Patients' Resistance to Chatbots for Anamnesis
Proceedings of the Special Interest Group on Adoption and Diffusion of Information Technology (DIGIT) (Pre-ICIS Workshop), Munich, Germany
Best Paper Award

Müller, L., Mattke, J., Maier, C., Weitzel, T., and Graser, H. (2019)
Chatbot Acceptance: A Latent Profile Analysis on Individuals' Trust in Conversational Agents
Proceedings of the 19th ACM SIGMIS Conference on Computers and People Research, Nashville, Tennessee, USA

Mattke, J., Müller, L., and Maier, C. (2019)
Paid, Owned and Earned Media: A Qualitative Comparative Analysis Revealing Attributes Influencing Consumer's Brand Attitude in Social Media
Proceedings of the 51th Hawaii International Conference on System Sciences (HICSS), Hawai (VHB-JOURQUAL 3 Rating: C)

Mattke, J., Maier, C., Müller, L., and Weitzel, T. (2018)
Bitcoin resistance behavior: a QCA study explaining why individuals resist bitcoin as a means of payment
Proceedings of the 39th International Conference on Information Systems (ICIS), San Francisco (VHB-JOURQUAL 3 Rating: A)

Müller, L., Mattke, J., and Maier, C. (2018)
Online Advertising Research Through the Ad Delivery Process: A Literature Review
Proceedings of the 18th ACM SIGMIS Conference on Computers and People Research, Buffalo-Niagara Falls, New York, USA

Müller, L., Mattke, J., and Maier, C. (2018)
#Sponsored #Ad: Exploring the Effect of Influencer Marketing on Purchase Intention
Proceedings of the 24th Americas Conference on Information Systems (AMCIS), New Orleans, Louisiana, USA (VHB-JOURQUAL 3 Rating: D)

Mattke, J., Müller, L., and Maier, C. (2018)
Why do Individuals Avoid Social Media Advertising: A Qualitative Comparison Analysis Study
Proceedings of the 26th European Conference on Information Systems (ECIS) (VHB-JOURQUAL 3 Rating: B)

Mattke, J., Müller, L., Maier, C., and Graser, H. (2018)
Avoidance of Social Media Advertising: A Latent Profile Analysis
Proceedings of the 18th ACM SIGMIS Conference on Computers and People Research

Mattke, J., Müller, L., Maier, C., and Weitzel, T. (2017)
Engagement with Social Ads: Explaining the Influence of Herding in Social Media Advertising
Proceedings of the Special Interest Group on Adoption and Diffusion of Information Technology (DIGIT) (Pre-ICIS Workshop), Seoul, South Korea
Research in Progress
Best Paper Nominee

Müller, L., Mattke, J., Maier, C., and Weitzel, T. (2017)
The Curse of Mobile Marketing: A Mixed Methods Study on Individuals' Switch to Mobile Ad Blockers
Proceedings of the 38th International Conference on Information Systems (ICIS), Seoul, Korea (VHB-JOURQUAL 3 Rating: A)

Mattke, J., Müller, L., and Maier, C. (2017)
Why do individuals block online ads? An explorative study to explain the use of ad blockers
Proceedings of the 23rd Americas Conference on Information Systems (AMCIS), Boston, Massachusetts, USA (VHB-JOURQUAL 3 Rating: D)