Essays on Technology Paternalism: Paternalistic Effects of Smart Technologies on User Behavior

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Kurzfassung (english version below)

Smarte Produkte wie Alexa-Lautsprecher von Amazon oder smarte Staubsauger von iRobot prägen zunehmend unseren Alltag. Algorithmen befähigen diese Geräte, autonom zu arbeiten und Entscheidungen unabhängig vom Nutzer zu treffen. Durch diese zunehmende Autonomie gewinnen diese Produkte auch die Fähigkeit, den Nutzer auf emotionaler Ebene zu beeinflussen. Wenn smarte Produkte wie Eltern schützend eingreifen und/oder Aktionen des Nutzers verhindern oder beeinflussen, greift das in die Autonomie und Kontrolle des Nutzers ein. Nutzer können sich durch die Aktionen der Produkte beispielsweise bevormundet fühlen; ein Konzept, dass Bevormundung durch Technologien (sogenannter Technologiepaternalismus, kurz TP) genannt wird. Trotz seiner zunehmenden Bedeutung, insbesondere mit dem Aufkommen smarter Systeme, ist TP in der Forschung zur Technologieakzeptanz und -resistenz noch nicht ausreichend erforscht. Diese Arbeit fasst die Erkenntnisse aus drei aktuellen Papern zusammen, um die vielschichtigen Beziehungen zwischen TP, Technologieakzeptanz und -resistenz zu beleuchten und aufzuzeigen, wie sich die wahrgenommene Bevormundung durch smarte Produkte auf die Produktakzeptanz der Nutzer auswirken kann.

Auf der Grundlage eines theoretischen Rahmens, der sich auf die Psychological Reactance Theory stützt, und empirischer Belege präsentiert diese Dissertation ein nuanciertes Verständnis der Auswirkungen von TP auf die Wahrnehmung von smarten Produkten durch die Nutzer. Es wird eine validierte Drei-Faktoren-Skala zur Messung von TP vorgestellt, die ein neuartiges Messinstrument für die künftige Forschung darstellt und eine Grundlage für kritische Diskussionen über das Design smarter Produkte bietet.

Die Ergebnisse aller drei Paper unterstreichen das heikle Gleichgewicht, das smarte Technologien zwischen der Unterstützung der Nutzer und der Wahrung ihres Gefühls von Kontrolle und Freiheit schaffen müssen. Da intelligente Produkte immer mehr in das tägliche Leben integriert werden, ist das Verständnis und die Bewältigung der Herausforderungen durch TP entscheidend für die Förderung der Technologieakzeptanz und die Minimierung der Resistenz. Marketing und Produktentwicklung sollten bei der strategischen Planung von Produktmerkmalen und -funktionen TP im Fokus behalten und gleichzeitig einen erhöhten Produktnutzen nicht aus den Augen verlieren.

Abstract

Smart products are progressively shaping our daily experiences, with algorithms empowering devices to operate autonomously, make decisions independently of users, and potentially compromise user well-being. This burgeoning autonomy in smart technologies has given rise to the concept of Technology Paternalism (TP), where devices act in a protective manner akin to a parental figure, potentially infringing on user autonomy and control. Despite its growing relevance, especially with the advent of increasingly smart systems, TP remains underexplored in technology acceptance and resistance research. This thesis synthesizes insights from three recent papers to elucidate the multifaceted relationship between TP, technology adoption and resistance, highlighting how perceived paternalism by smart products can impact user behavior.

Drawing from a theoretical framework informed by psychological reactance theory and empirical evidence from correlational studies, this synthesis presents a nuanced understanding of TP's implications for user autonomy, control, and resistance to smart technologies. It introduces a validated three-factor scale for measuring TP providing a novel tool for future research and offering a basis for critical discussions on smart product design and policy making.

The collective findings underscore the delicate balance smart technologies must navigate between aiding users and preserving their sense of control and freedom. As smart products become more embedded in daily life, understanding, and addressing the challenges posed by TP is crucial for fostering technology acceptance and minimizing resistance, thereby guiding marketers and product developers in strategizing product features and functionalities that keep TP in mind while delivering enhanced benefits.

Danksagung (english version below)

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CHAPTER

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INTRODUCTION

1. Introduction

K.I.T.T.: [ejecting Michael Knight through the ejection seat] "Sorry Pal, forgive me!"
Michael Knight: [realizing that he was being ejected against his will] "What?! K.I.T.T!?"
Knight Rider Episode 1 Season 3 "Knight of the Drones"
(Foster & Sanford, 1984)

The quote above is from the TV show Knight Rider from the 1980s. This was (at least for people of my age) one of the most famous TV shows of that time. One reason for this (besides the easy-to-follow storylines) was the teamwork between a human (Michael Knight) and a smart technology (K.I.T.T.; a smart and armored car with the ability to speak to its driver and act autonomously). Back then, smart cars with autopilot and the ability to talk to the driver were science fiction. This is no longer the case; Cruise LLC, the first autonomous taxi service, began transporting passengers for profit without an actual human driver in June 2022 (Kolodny, 2022), and voice-based human–computer interaction became commonplace with the introduction of smart voice-based assistants such as Amazon's Alexa, which is accessible on a variety of devices, totaling hundreds of millions worldwide (Amazon, 2024). These advances have resulted in artificial intelligence (AI) systems that are increasingly capable of understanding context, paving the way for more natural and human-like interactions in applications such as chat bots, virtual assistants, and language translation.

Back to Knight Rider. Throughout the series, Michael Knight humanizes K.I.T.T., a phenomenon called anthropomorphism, which potentially increases product attachment (Yuan & Dennis, 2019). For example, the episode "Junk Yard Dog" shows the depth of Michael's attachment to K.I.T.T. After the car is severely damaged, the episode delves into Michael's efforts to rebuild it, highlighting the emotional bond between him and his car (Valvin, 1985). Michael Knight and K.I.T.T. become "friends," so K.I.T.T. has established itself as a social entity in its relationship with its driver, affecting his emotions and developing agency by interacting in a human-like manner. The quote above underscores this, as K.I.T.T. demonstrates its autonomous ability to protect Michael Knight, even against his will, by activating an ejector seat. What was fun in a TV show in the past may now be uncomfortable for today's users. Aside from the extreme example of the ejection seat (due to the narrative tension of the TV show), how would a driver today feel about a car telling them what to do or not do (e.g., obey speed limits)? Especially if the user is emotionally attached to the car (or any other smart product) because of its anthropomorphism? And beyond the Knight Rider analogy, how would someone feel if smart products knew what was right and wrong based on their algorithms and forced the user to obey rules while interacting with them in a human-like way? It is reasonable to assume that these situations may strongly influence the intention to use, buy, or resist such technology.

Hence, a key challenge associated with emerging smart technologies is the complexity of identifying critical factors that influence potential users' decisions to adopt or reject them (W. M. Lim & Ting, 2012). According to technology adoption research, the way users adopt these products is dependent on several personal or product-related factors, such as perceived usefulness, perceived ease of use, usage experience, and voluntariness (Venkatesh, 2022). Davis (1989), Venkatesh et al. (2012), and Ajzen (1991) (among others) have established that such factors have a strong influence on technology adoption intention. Technology resistance is also a significant factor in product adoption (H.-W. Kim & Kankanhalli, 2009; Schein & Rauschnabel, 2021). Smart products, such as self-driving taxis, have disrupted traditional business models and introduced novel factors that influence consumer adoption choices (Raff & Wentzel, 2018). Besides offering more functionality, these products may be perceived as social agents (like K.I.T.T.), impacting users emotionally and psychologically (Shang et al., 2012; van Doorn et al., 2017). It is important to investigate the emotional and psychological precursors that drive users to embrace or reject smart products (Marikyan et al., 2019). These emotional and psychological factors deviate significantly from the presumed determinants in traditional acceptance and resistance theories, such as the Technology Acceptance Model (TAM; Davis, 1989) or the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2012). These established theories do not consider emotional or psychological factors as driving forces in technology adoption and resistance.

To return to the Knight Rider analogy one last time, if a car knows what is right and what is wrong, and it prevents the driver from performing a (potentially) harmful action (by ejecting them) against their will (Michael Knight actually wanted to stay in the car to handle a dangerous situation manually), this potentially increases the usefulness and user value (as it increases user safety), but the car may also be seen as acting like a parent, ultimately becoming paternalistic toward the user (Rochi, 2023; Spiekermann & Pallas, 2006). This phenomenon is called technology paternalism (TP; Rochi, 2023; Rochi et al., 2024; Spiekermann & Pallas, 2006). Apart from its initial definition by Spiekermann and Pallas (2006), this topic has not received much attention thus far. But with products in all areas becoming smart, TP gains importance with every milestone reached in AI research and development.

Since the above-mentioned theories do not consider phenomena such as TP, this thesis challenges the assumption of recent technology adoption theories that the more functional and useful a product is, the higher the intention to adopt it becomes. It contains three papers, of which significant portions have been submitted and published in scientific forums. This has led to the creation of peer-reviewed articles and conference presentations. Furthermore, all three papers have been (or will be) presented at various academic conferences at different stages of their development. The author of this dissertation is the main (or sole) contributor to all three papers.

Paper I, a semi-systematic literature review, builds a conceptual framework that connects other relevant constructs around it. It suggests that the conventional wisdom in technology adoption research, that more product support equals more value for the customer and consequently more adoption intention, is no longer entirely valid. To the best of the author's knowledge, the literature review was the first attempt to systematically analyze and structure knowledge from various disciplines about the phenomenon of TP and how it affects technology acceptance and resistance. This contributes to the body of knowledge in two main ways. To date, the subject of TP has been briefly mentioned without being situated within a theoretical framework. This paper establishes a theoretical foundation for understanding the connection between TP and the dynamics of technology adoption and resistance. Additionally, going beyond a purely descriptive analysis, the author employs psychological reactance theory to formulate propositions regarding how different facets of TP impact the stimulation of reactance, ultimately affecting alterations in technology adoption behavior and resistance. This review serves as the fundamental basis for Papers II and III (Chapters 3 and 4).

A solely conceptual approach does not allow the measurement of the examined phenomenon, which results in the demand for a measurement tool. Further, it is necessary to evaluate the dimensionality of TP empirically (as proposed in Paper I). Paper II picks up these open points by developing a validated measurement scale and evaluating how this scale behaves with established constructs from technology adoption research. It makes a valuable contribution by tackling the absence of empirical research into users' perceptions of TP. This is achieved through the development of a theoretically robust measurement scale designed to evaluate the extent to which TP is perceived. Furthermore, this publication presents initial empirical findings that highlight the connections between TP and its antecedents, related concepts, and outcomes.

Using the developed measurement scale, Paper III empirically examines whether consumers consider feelings of being patronized by a smart product and, if so, whether these feelings influence their intentions to adopt or resist smart products. This work also analyzes the role of two potential antecedents of TP: anthropomorphism and product autonomy. Paper III contributes to the literature by 1) enriching the field of research on new technologies, 2) fitting the concept of TP between technology adoption and resistance theories, and 3) giving further empirical evidence for the TP–behavioral intention/technology resistance relationships (see Table 1 for an overview of all three papers).

This thesis is divided into eight chapters. Chapter 1 contains the introductory section, which provides details on paternalism, TP, smart products, and the research problem. In Chapters 2 to 4, Papers I to III are presented in detail. Chapter 5 summarizes the overall results and discusses contributions, implications, and limitations, followed by the appendices (Chapter 0), references (Chapter 7) and the declaration of authorship (Chapter 0).

It is important to emphasize that each of the three papers can be examined independently, allowing for separate consideration. Consequently, there is some unavoidable redundancy and thematic overlap throughout the entire thesis. Readers are thus encouraged to review the comprehensive thesis for a broad understanding of the specific paper.

Important note: *For a better understanding of the affiliation of individual studies within each paper, the studies have been renumbered as "paper.study" within the respective paper (e.g., Study III.2 means the second study in Paper III).*

Table 1: Papers overview

Paper no.	I - Chapter 2 – Literature review	II - Chapter 3 – Scale development	III - Chapter 4 – Initial use of scale
Research objectives	- Definition and conceptualization of TP - Development of a theoretical framework for the relationship between TP, technology adoption, and resistance - Development of propositions about TP influences reactance arousal and technology adoption - Literature review from various disciplines about how TP affects technology acceptance and resistance	- Addressing the lack of empirical research on user perceptions of TP by developing a measurement scale - Use of qualitative and quantitative procedures to operationalize TP - Provision of preliminary empirical evidence for associations between TP and precursors, associated concepts, and consequences	- First use of the newly developed scale - Initial evidence on consequences of TP on usage intention and behavior - Initial evidence for potential moderating and mediating effects on the relationship of TP on behavioral intention (and others)
Key findings	- Provision of a new model identifying the dimensions and multiplicative characteristics of TP - Enriched understanding of how TP influences perceptions of smart products - Shedding light on the negative associations that certain characteristics of smart products may evoke in users	- Provision of a validated measurement scale - First empirical evidence of TP's impact on technology adoption and related constructs, such as technology autonomy, technology intrusiveness, perceived usefulness - Conceptualization of product autonomy as an antecedent of TP rather than a dimension of the same	- TP directly affects technology resistance and behavioral intention - The often-proposed positive effect of product autonomy and anthropomorphism on behavioral intention might not exist under all circumstances - The indirect effects of product autonomy and anthropomorphism on behavioral intention and resistance through TP - Personal attributes' moderating effect on TP
Key contributions	- Identification of the dimensions of TP and its multiplicative characteristics - Adding knowledge to the literature on technology acceptance and resistance - Enriching the understanding of how smart products can generate negative associations in users - The model's contribution to the literature on acceptance of and resistance to smart products by clarifying how the four dimensions of TP interact, cause reactance, and ultimately directly and indirectly influence product adoption	- Operationalizing TP, enhancing the evolving field of research on emerging technologies - A robust 16-item scale for TP, enabling consistent research outcomes in smart technology adoption - Allowing researchers to collect reliable and valid data, which is essential for conducting empirical studies on TP - Challenging the assumption "the more support the better" of established theories - Provision of empirical evidence for the TP–technology adoption relationship	- Enrichment of the field of research on new technologies - Fitting the concept of TP between technology adoption and resistance theories, showing the relationships between them and TP - Further empirical evidence for the TP–behavioral intention/technology resistance relationship
Theories used	- Psychological reactance theory - Technology acceptance/resistance theories	- Technology acceptance theories - Technology resistance theories	- Technology acceptance theories - Technology resistance theories
Sample size	- 110 publications reviewed	- Total: N = 608 - Study II.4: N = 282 - Study II.5: N = 326	- Total: N = 1223 - Study III.1 N = 271 - Study III.2 Pre-test: N = 191 - Study III.2: N = 311 - Study III.3: N = 450
Methodology	Literature review and conceptualization	Quantitative and qualitative scale development	Structural equation model, mediation, and moderation analysis
Publication status	Published: Rochi, M. (2023). Technology paternalism and smart products: Review, synthesis, and research agenda. Technological Forecasting and Social Change, 192, 122557.	Published: Rochi, M., Rauschnabel, P. A., Renner, K.-H., & Ivens, B. S. (2024). Technology paternalism: Development and validation of a measurement scale. Psychology & Marketing, 1–17.	In the stage of final preparation of submission
Journal ranking	VHB Jourqual 4: B / ABDC: A	VHB Jourqual 4: B / ABDC: A	n/a
Previous versions presented at:	- Irish Acad. of Management Conference, Dublin 2019 - Intl. AR/VR Conference, Munich 2019	- AIRSI Conference 2022 (online) - 7th Intl. XR Conference, Lisbon 2022 - 8th Intl. XR-Metaverse Conference, Las Vegas 2023	Not yet presented; submitted for AMA Summer Conference, Boston 2024

Note: VHB = Verband der Hochschullehrerinnen und Hochschullehrer für Betriebswirtschaft e.V. (German Academic Association for Business Research); ABDC = Australian Business Deans Council; Information on rankings sourced from the respective association websites

1.1 Paternalism and technology paternalism

Paternalism is an "intriguing, complex and controversial" (Aycan, 2006, p. 445) construct in the management literature. This is underlined by several attempts to define it. For example, Dworkin (2020) defined it as a concept that involves one party intervening in another's affairs against their will with the intention of safeguarding their well-being.[1] Another definition includes two necessary conditions: 1) the paternalistic action is primarily intended to benefit the recipient, and 2) the recipient's consent or dissent is not a relevant consideration for the initiator (Hershey, 1985). A third definition designates paternalism as "attitude and practice that are commonly, though not exclusively, understood as an infringement on the personal freedom and autonomy of a person (or class of persons) with a beneficent or protective intent" (Thompson, 2013). Hence, paternalism is concerned with the welfare of a person subjected to an intervention and can be characterized as a form of behavior (Clarke, 2002). All these definitions include a cut of personal autonomy and a certain degree of welfare intention of the patron. This cut of personal freedom can be perceived as detrimental and can lead to counterproductive responses (Daniels & Jordan, 2019; Farh & Cheng, 2000). Paternalism can be perceived in situations such as business, family settings, or human–government interactions. Examples include a country's civil law not allowing the enforcement of certain kinds of contracts, such as gambling debts (Dworkin, 2020); a father's decisions for his children about how long to play video games; or a supervisor offering guidance to subordinates, both professionally and personally, in a fatherly manner (Aycan, 2006).

In the early 2000s, a novel and significant perspective called "libertarian paternalism" emerged, drawing from behavioral science insights into our cognitive and emotional shortcomings. Thaler and Sunstein (2003) highlighted these insights' importance and proposed nudging individuals toward their own objectives by subtly structuring choices to increase the likelihood of desirable outcomes. They defined such nudging as any subtle aspect of choice architecture that predictably alters behavior without limiting options or significantly modifying economic incentives. Dworkin (2020) underlined that nudges differ from traditional paternalism by not eliminating or coercively altering choices but by modifying how options are presented, making beneficial choices more appealing. The essence of nudging involves subtle interventions that guide choices without restricting them. Early examples include positioning healthier foods at eye level in cafeterias to encourage

[1] In this work, Dworkin's (2020) definition is used.

better eating habits and implementing opt-out retirement savings plans to increase participation rates. These interventions contrast with merely providing information, aiming instead for a broader influence on behavior. The discussion of paternalism outlined in this thesis raises the question of whether nudging can be deemed paternalistic. The initial criterion for paternalism is that an act (or failure to act) must encroach upon the freedom or self-determination of an individual. This nudging aspect is not mirrored in the previously mentioned definitions of paternalism and is therefore not the subject of this work. For instance, affixing a warning label to a cigarette package does not impinge on the freedom or autonomy of a smoker.

Paternalism can manifest in interactions with smart products as well, as they can make judgments about right and wrong based on information and, in turn, constrain people's actions, thereby adopting a paternalistic role (Rochi, 2023; Spiekermann & Pallas, 2006). Building upon the research by Spiekermann and Pallas (2006), TP is characterized as an autonomous action of a technology that is claimed to be in the interest of the user, directly affects them, is perceived as limiting freedom, and cannot be overruled without sacrificing functionality. It is worth noting that while the definition by Spiekermann and Pallas (2006) incorporates autonomy as a dimension of TP, in this thesis, from Paper II onwards, the author asserts that product autonomy is a prerequisite for TP (Rochi, 2023). This is because intelligent technologies inherently operate autonomously or independently (Raff et al., 2020). Hence, in the absence of autonomy, technology can only act on behalf of the user or perform actions initiated by the user, thereby excluding the possibility of TP. An example of a paternalistic technology could be a smart home device that automatically adjusts thermostat settings based on what it perceives as the user's comfort level. While the intention behind this technology may be to optimize the user's comfort and energy efficiency, it limits the user's freedom to control the temperature manually. Additionally, if the user wants to override the device's settings, they may have to sacrifice the convenience of having the device automatically adjust the temperature, thus exemplifying the characteristics of TP outlined in the definition. The example of a smart thermostat may seem relatively harmless, and the autonomy cut and lack of overruling prospects may not be strongly pronounced. But considering recent technological advancements, there are many potential paternalistic scenarios with smart technologies. A more futuristic example might be a smart speaker that does not allow you to listen to your favorite songs at a volume level comfortable for you because it deems this too loud for your ears.

Observing the potential for paternalistic design associated with smart technologies, an enticing degree of influence over human behavior looms. It is important to note that this power is not inherent in the technology itself; a smart technology simply adheres to the rules embedded in its algorithms. Consequently, some questions emerge: "Who will be the real patrons behind TP if it were to become a reality? Who will decide about the rules, the 'rights' and 'wrongs' of every-day actions? And what are the real interests behind a paternalistic technology?" (Spiekermann & Pallas, 2006, p. 12). Spiekermann and Pallas (2006) discussed three groups of potential patrons behind TP: software engineers, marketers of smart technologies, and regulators who influence application design.

First, software engineers play a pivotal role in shaping paternalistic technology attributes as they implement rules and regulations by coding the necessary algorithms (Millar, 2015). Engineers rarely operate in isolation; usually, they merely execute directives provided by their employers or other colleagues, such as the marketing or market research department. Consequently, corporate financial gains could emerge as a primary motivator for designing paternalistic products. An example of this would be marketers, for instance, deciding to sell certain products only in bundles, ensuring that one product does not work without others (Spiekermann & Pallas, 2006). An example of paternalistic product management would be a requirement to exclusively purchase from original equipment manufacturers to ensure compatibility. Cars might be designed in a manner that permits repairs only with spare parts from the original manufacturer.

These scenarios underscore the challenging balance that needs consideration when contemplating a potential paternalistic technology design. Here, a third group of potential patrons may emerge: regulatory bodies. It is not easy to separate TP from simple governmental regulations implemented in smart product development. If a regulation enforces a maximum volume level for smart speakers, should the technical realization be seen as TP or as law enforcement (Spiekermann & Pallas, 2006)? One example of paternalistic law introduction is mandatory bicycle helmet laws that require cyclists, regardless of age, to wear helmets.

Besides the importance of understanding that technologies only represent the morals and underlying goals of developers, marketers, or governmental regulations, it is necessary to appreciate and evaluate how potential paternalistic technological attributes affect product adoption and consumer well-being. It is not the goal of this dissertation to investigate "who are the real patrons" (Spiekermann & Pallas, 2006). Rather, this dissertation intends to shed light on the question of how users perceive TP and how it affects user behavior, such as through product adoption and resistance.

1.2 Smart products

The landscape of products is undergoing a revolution propelled by information technology. Traditionally comprising only mechanical and electrical components, products have evolved into intricate systems that integrate hardware, sensors, data storage, microprocessors, software, and connectivity in diverse configurations. These smart products represent a paradigm shift facilitated by substantial enhancements in processing power, the miniaturization of devices, and the widespread advantages of wireless connectivity (Porter & Heppelmann, 2014).

The term "smart product" has become increasingly popular in science, practice, and politics. Only a few years ago, these products were only discussed in philosophical debates or used as examples of cutting-edge technology (Raff et al., 2020). However, with technological improvements, smart products have become a reality, disrupting traditional markets (like the taxi industry with smart, driverless taxis). However, the existing body of research on smart products reveals a lack of consensus and clarity regarding the precise definition of a smart product (Raff et al., 2020). Various terms, such as intelligent products (Raff & Wentzel, 2018), smart technologies (Roy et al., 2018), smart things (Püschel et al., 2016) or smart connected products (Porter & Heppelmann, 2014, 2015) have been employed interchangeably. For the purposes of this dissertation, all of these terms are considered synonymous, and these products are defined as devices that are capable of learning, anticipating, and acting independently of user intervention (Raff et al., 2020), as well as consisting of a physical and a digital part (Pardo et al., 2020). A smart product has to "address usage on its own" (the physical part; Pardo et al., 2020, p. 207) and connect with a larger network (Raff et al., 2020) to interact with other smart products or humans (Monostori et al., 2016).

In the digital domain, smart products make decisions autonomously and manage interactions with external entities (Sánchez López et al., 2012). They exhibit a diverse set of capabilities that transcend conventional product boundaries, categorizable into four key areas: monitoring, control, optimization, and autonomy (Porter & Heppelmann, 2014). The integration of monitoring, control, and optimization functionalities enables smart, connected products to attain a level of autonomy that was previously unattainable (Porter &

Heppelmann, 2014). These capabilities empower smart products to engage with humans in a natural and initiative-taking manner, to offer assistance in task performance, to proactively address issues, and to collaborate with humans and other products. Such collaboration involves leveraging resources from the environment or interfacing with other smart products (d'Aquin et al., 2012). By collaborating with other systems and products, the significance of product capabilities can experience exponential growth with increasing interconnectivity. This connectivity enables utilities to gather insights and respond to evolving demand patterns over time (Porter & Heppelmann, 2014). Smart products can function with complete autonomy by employing algorithms that analyze data pertaining to their performance and surroundings. This includes information about the activities of other products in the network, and they utilize their communication capabilities to interact with those products (Porter & Heppelmann, 2014).

From a marketing perspective, the rise of smart products necessitates a reevaluation of product attributes and ecosystems and the development of new strategies to navigate the changing nature of products (Pardo et al., 2020). These products necessitate the establishment of novel customer relationships, demanding updated marketing practices and skill sets. Through the accumulation and analysis of data on product usage, companies acquire valuable insights into the ways products create value for customers. This capability facilitates improved positioning of offerings, more effective communication of product value to customers, advanced market segmentation, customization of product and service bundles to enhance value for each segment, and strategic pricing of these bundles to capture a larger share of that value (Porter & Heppelmann, 2014).

The advancements in technology and enhanced opportunities to enhance customer value and improve marketing are evident in the expanding market share of smart products. The smart home sector, including devices such as smart meters, is anticipated to experience an annual growth rate surpassing 11% from 2022 to 2028, resulting in a market volume of $231.6 billion by 2028 (Statista, 2023). Predictions indicate that consumer spending on smart home products and services will exceed $170 billion by 2025, and the global number of households equipped with smart home systems will surpass 400 million (Strategy Analytics, 2021).

1.3 Research problem

As seen above, paternalism can be observed in the use of smart products that can judge situations as either appropriate or inappropriate and subsequently influence user behavior. This dynamic places these smart devices in a paternalistic role as they guide or limit the actions of individuals based on their programmed understanding of what is considered correct or incorrect (Rochi, 2023; Spiekermann & Pallas, 2006).

Nevertheless, knowledge on this topic is limited and lacking empirical evidence and conceptual models. One overarching goal of this thesis is to describe and characterize this construct. As TP is strongly related to the way users perceive and interact with smart technologies, technology acceptance and resistance build a suitable frame to analyze and approach the topic. To outline the core points of this dissertation, highlight the research problem, and establish the overarching research questions, this section examines the existing understanding of technology adoption and resistance in a broader context. It identifies the gaps in the literature, paying particular attention to the omission of smart technologies and their paternalistic aspects.

Technology adoption has attracted manifold research attempts to understand how and why users adapt technologies. In the realm of information systems, the adoption of technology stands out as one of the most thoroughly investigated subjects (Salahshour Rad et al., 2018). Technology adoption is defined as "a sociological model that describes the adoption or the acceptance of a new product or an innovation according to the demographic and psychological characteristics of defined adopter groups" (Z. Xu et al., 2021, p. 1). Research focused on technology adoption seeks to comprehend, forecast, and elucidate the factors that impact adoption behavior at both individual and organizational levels, fostering the acceptance and utilization of technological innovations. These investigations have contributed to the formulation of conceptual models and frameworks that elucidate the connection between these variables and adoption behavior. For investigations of the adoption of technologies, various theories have been used, such as the Theory of Reasoned Action (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975), the Theory of Planned Behavior (Ajzen, 1991; Bosnjak et al., 2020) and the Diffusion of Innovations theory (Rogers, 1962). These theories explicate user beliefs, attitudes, intentions, and the actual use of systems and serve as the basis of further detailed technology adoption models. Among others, two models have attracted a great deal of attention in the literature: Davis' widely recognized Technology Acceptance Model (TAM; Davis, 1985) and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003).

The **TAM** is rooted in the Theory of Reasoned Action (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975). In its basic formulation, the TAM suggests that perceived ease of use, perceived usefulness, attitude toward use, and behavioral intention collectively forecast the actual usage of a technology. It has been subject to several review articles, including Hsiao and Yang (2011), Marangunić and Granić (2015), and Mortenson and Vidgen (2016), which underline the academic and practical impact of TAM. In Davis, Bagozzi, and Warshaw's rendition of TAM (Davis et al., 1989), emphasizing the significance of intentions is crucial. In this version, usage behavior (i.e., actual use of the system) represents a direct outcome of behavioral intention. Behavioral intention, in turn, is shaped by attitude toward usage, representing favorable or unfavorable sentiments regarding technology use, and perceived usefulness, indicating the belief that utilizing the technology will enhance performance. Overall, TAM's simplicity has been demonstrated as a valid and potent method for elucidating technology acceptance, and is applicable across a range of technologies and contexts (Momani et al., 2018). One shortcoming of TAM is that it does not take into account the impact of social factors on behavior—variables that have been demonstrated to exert a significant influence on usage behavior (Granić, 2023).

In contrast, these variables are integral determinants of behavior in the Theory of Planned Behavior (Ajzen, 1991), in which social influences are modeled as determinants of behavioral intention and perceived behavioral control is modeled as a determinant of both behavioral intention and behavior. This led to the development of further enriched TAM concepts, such as the augmented TAM (Taylor & Todd, 1995) and the extended TAM (Venkatesh & Davis, 2000), to offer a more comprehensive examination of the crucial determinants of technology usage. TAM and its extensions have been utilized extensively to clarify smart product usage intentions across various domains, including smart healthcare systems (Y. Chen et al., 2017; Hsieh, 2015), intelligent learning environments (Cabada et al., 2018), smart advertising systems (Aguilar & Garcia, 2018), and robots (Liang & Lee, 2017).

Another notable refinement and extension of the TAM is the well-established **UTAUT** model (Venkatesh et al., 2003), which introduces three primary constructs that directly influence behavioral intention: performance expectancy, effort expectancy, and social influences. Additionally, behavioral intention and facilitating conditions serve as predictors of actual behavior (e.g., actual usage). Despite criticisms regarding the model's excessive number of independent variables for predicting intentions and behavior (Bagozzi, 2007), it is considered robust in assessing and forecasting technology acceptance (Venkatesh et al., 2003). This model has also evolved. The extended UTAUT2 model emphasizes the consumer's usage context (Venkatesh et al., 2012) and introduces three new constructs that directly influence behavioral intention: hedonic motivation, price value, and habit. In addition to behavioral intention and facilitating conditions, the model posits habit as an additional predictor of usage. UTAUT and UTAUT2 have been used in the analyses of intelligent games (Hamari & Koivisto, 2013), agent-based systems (T. Zhang & Zhang, 2007), intelligent healthcare systems (Fan et al., 2020), learning systems (Fernández-Llamas et al., 2018), and recommender systems (Oechslein et al., 2014), resulting in a substantial body of knowledge dedicated to system acceptance of smart and innovative products. These studies consistently reveal associations among beliefs, attitudes, behavioral intentions, and usage behavior, with a predominant focus on the initial decision of whether to adopt a technology (Venkatesh et al., 2003).

Comparatively less attention has been paid to individual **resistance to technologies** and their subsequent use (H.-W. Kim & Kankanhalli, 2009; Lapointe & Rivard, 2005), even though "consumer resistance towards innovation is an aspect of consumer behaviour that is as important as acceptance and adoption" (Talwar et al., 2020, p. 286). Technology resistance research is dedicated to elucidating the reasons behind individuals rejecting technologies (Lapointe & Rivard, 2005). There is a lack of analyses concerning the factors that lead to individual rejection (Venkatesh & Brown, 2001) and a lack of a common understanding of user resistance (Laumer & Eckhardt, 2012). Technology resistance is not yet consistently defined. For instance, Schein and Rauschnabel (2021, p. 3346) defined it as "a person's proactive intention to resist using a technology," and Raff et al. (2024, p. 3) stated that "in contrast to acceptance, which represents factual behavior, resistance can be understood as a cognitive force that precludes such behavior." Minimal resistance does not imply a desire to use a technology, and elevated resistance suggests that individuals may attempt to avoid using a technology (e.g., due to potential job threats), even if they acknowledge its utility (e.g., in automating certain tasks) (Schein & Rauschnabel, 2021). Put differently, technology resistance research contends that, contrary to the fundamental assumptions of the acceptance theories introduced above, new technologies are not inherently advantageous for users (Markus, 1983; Saga & Zmud, 1993). Hence, resistance and acceptance do not represent opposing ends of a spectrum, and resistance should not be equated with low acceptance; a lack of acceptance may simply indicate user indifference toward a technology rather than active opposition, such as when users fail to perceive its utility.

Unlike many acceptance theories, resistance research does not operate on the assumption that new technologies are inherently beneficial for the user (Markus, 1983; Saga & Zmud, 1993). Instead, it is grounded in the principle that individuals seek psychological equilibrium (Heider, 1958; Newcomb, 1953; Osgood & Tannenbaum, 1955). According to resistance research, any imposed technology has the potential to disrupt this equilibrium. Consequently, individuals may opt to resist the change rather than undergo the disruptive process of readjustment (Talke & Heidenreich, 2014).

Research has identified various mechanisms that contribute to resistance, such as fear of job loss (Spreer & Rauschnabel, 2016), loss of routine (Joshi, 1991; H.-W. Kim & Kankanhalli, 2009; Marakas & Hornik, 1996; Spreer & Rauschnabel, 2016), and psychological risks (Cunningham, 1967), among others. Salespeople might exhibit reluctance to alter a routine rather than outright rejection of a technology due to perceived usefulness issues (Spreer & Rauschnabel, 2016). Several studies have validated and broadened this perspective. For instance, Lapointe and Rivard (2005) presented a dynamic multi-level model that elucidates resistance as a progression occurring at both the individual and unit levels. H.-W. Kim and Kankanhalli (2009) combined insights from status quo bias theory (Samuelson & Zeckhauser, 1988), TAM, and the equity-implementation model (Joshi, 1991) to attain a more profound understanding of users' perceptions of change.

Despite its crucial impact and significance, there has been – compared to TAM and UTAUT approaches – relatively limited research focus on consumer resistance to smart products. Examples from a small body of knowledge on smart product consumer resistance include smartwatches (Mani & Chouk, 2017), organic food (Kushwah et al., 2019), internet banking (Laukkanen, 2016), green products (Claudy et al., 2010), mobile sales assistants (Cho & Chang, 2008), apps (Prakash & Das, 2022), medical information technology (Bhattacherjee & Hikmet, 2007), and online teaching platforms (Craig et al., 2019). The central concepts employed in these research attempts encompass product attributes such as perceived usefulness, complexity, and perceived benefits (Mani & Chouk, 2019). Examining resistance to smartphone usage, Abbas et al. (2017) identified that the dominant predictors of resistance included product characteristics such as price, complexity, and social influence. Similarly, Mani and Chouk (2017) and Raff and Wentzel (2023) observed that perceived product intrusiveness influenced resistance to smart products. Raff and Wentzel (2023) also identified inhibitors of smart technology adoption, such as the feeling of constant observance, loss of control, and concerns about artificial intelligence and autonomy.

Many studies on technology acceptance operate under the assumption that individuals are generally open to new technologies (e.g., Moriuchi, 2019). Critics argue that adoption research has been limited in scope by focusing solely on the advantages of embracing innovative technology (C.-K. Park et al., 2014). This pro-innovation bias often conceals the reality of substantial failure rates in high-tech innovation (Castellion & Markham, 2013; Talke & Heidenreich, 2014). Past research has established that perceived risks play a notable role in influencing the adoption trajectory of innovative technologies (D. Y. Lee & Lehto, 2013; M.-C. Lee, 2009). From this perspective, resistance from consumers and rejectionist attitudes emerge as significant factors contributing to such failures (Talke & Heidenreich, 2014).

Smart technologies have the potential to function as social agents, influencing users on emotional or psychological levels (Shang et al., 2012; van Doorn et al., 2017), when they "acquire the agencies to spill semantically distinct traces onto the material world and detour their human interlocutors into an object-mediated entanglement" (Mitew, 2014, p. 7). Hence, smart products build "anticipatory materiality acting as a host to human interlocutors" (Mitew, 2014, p. 10). It is necessary to explore the emotional and psychological factors that prompt users to embrace or reject smart products (Marikyan et al., 2019). These factors differ significantly from the elements established in traditional acceptance theories. Recent research endeavors have introduced factors like user well-being and happiness (Attié & Meyer-Waarden, 2022; Whillans et al., 2020), trust (Vimalkumar et al., 2021) or discomfort and insecurity (Chang & Chen, 2021). Similarly, some researchers advocate considering the effects of autonomy loss resulting from the use of smart products (Chi et al., 2020; Raff & Wentzel, 2023; Schein & Rauschnabel, 2021). However, recent publications utilizing established theories (such as TAM or UTAUT) in the context of smart product adoption or resistance often overlook these barriers (e.g., C. Chen et al., 2017; Tu et al., 2022; Yu & Huang, 2020). This oversight may arise from the (above outlined) limitations of established theories in fully comprehending emerging technologies such as smart products (Shahab et al., 2021).

One of these overlooked barriers to the adoption of smart products is TP (Rochi, 2023). We are surrounded by potentially paternalistic technologies that can understand our context and make judgments about what is right or wrong (Spiekermann & Pallas, 2006). As smart and context-aware products are relatively new to customers and less extensively researched than traditional products such as tablets or computers, only a limited number of studies have explicitly addressed TP and its various aspects before this dissertation project (e.g., Kinder et al., 2008; Spiekermann & Pallas, 2006). An exceptional instance of empirical work on TP is Schein and Rauschnabel's (2021) identification of a paternalism factor positively (negatively) correlated with technology resistance (technology acceptance).

Furthermore, traditional acceptance models assume a linear relationship, positing that the more supportive a product is, the higher its perceived usefulness and, consequently, the greater its acceptance. These models are additive models, which means that an infinite increase in perceived usefulness should lead to an infinite amount of adoption intention because in an additive model, one independent variable, positively affecting usefulness, can compensate for all other negative independent variables. This is somewhat typical of this type of technology adoption model, but it is not entirely plausible and may not accurately reflect the reality of smart products. For instance, a smart product offering excessively detailed or cumbersome advice may be perceived as paternalistic, potentially leading to a decrease rather than an increase in perceived usefulness. Furthermore, the conventional assumption in technology adoption research, which presumes that "more support leads to better outcomes" or "the more functionality the better," no longer remains valid (Rochi, 2023). The level of product smartness has both positive and negative implications for adoption, but in recent years, scholars have somewhat neglected the negative effects of increasing product smartness as a significant influencing factor. Consistent with traditional technology adoption research, factors such as the welfare intention of smart products and product autonomy may positively influence perceived usefulness and ease of use but may also increase resistance due to a perceived reduction in autonomy or loss of control.

To further understand this issue, it is important to conceptualize the phenomenon of TP and to understand how it has been researched in the past. To pave the way for empirical research and evidence of the phenomenon, the development of a measurement tool is also necessary to enable researchers to quantify and empirically analyze TP. With a newly developed scale, a standardized and comparable way to assess and compare paternalistic aspects of different technologies and how they influence users is possible. This comparability is crucial for drawing meaningful conclusions, generalizing findings to broader populations, enriching the body of knowledge, and empowering future research attempts. Considering the difficulties described regarding the current conceptualization and measurement of TP, it is difficult to analyze more complex issues, such as the causes or consequences. Therefore, research is required to determine how to best conceptualize and measure TP and answer research questions using this new measure. Knowing the causes of TP could provide important indicators of how to decrease the perception of this phenomenon, and possibly enhance product acceptance and usage intention. Thus, a new measure can serve basic and applied research alike.

In summary, the objective of this thesis is to enhance the manageability of TP for both theoretical understanding and practical application. This is achieved by incorporating insights from recent research on this topic. The fundamental goal is to conceptualize TP and create a measurement scale that is both valid and reliable. Additionally, this dissertation delves into the causes and consequences of TP and explores related moderating and mediating effects. The research questions guiding this thesis are as follows:

I. How has the phenomenon of technology paternalism been defined, conceptualized, and measured in previous literature?
II. How can TP best be defined considering the recent body of knowledge and the recent development of smart products?
III. How does TP affect theoretical models, namely behavioral intention and technology resistance, and how does it fit between these theoretical models?
IV. How can TP be measured considering the recent body of knowledge and the recent development of smart products?
V. What are the potential antecedents and consequences of TP?
VI. What consequences does TP have for individuals' usage intentions, technology resistance, and actual behavior?
VII. What are the possible moderators and mediators of the effects of TP on behavioral intention and technology resistance?

Within the next three chapters, this thesis strives to answer these research questions.

CHAPTER

2

PAPER I

Technology paternalism and smart products: Review, synthesis, and research agenda

2. Paper I: Technology paternalism and smart products: review, synthesis, and research agenda[2]

Abstract

Artificial intelligence is increasingly influencing our daily lives. Algorithms enable objects to act autonomously, make decisions without the user's consent, and thus threaten the user's well-being in various ways. This can result in the perception of technology paternalism (TP). Although TP is a highly relevant issue in technology acceptance research, it has been largely ignored in recent scientific debates. Recent technology adoption research (such as the technology acceptance model) has largely ignored this issue. Very little is known about how smart products affect users' perceptions of autonomy and control, and how this affects product evaluation. This paper summarizes and discusses the state of knowledge on TP and develops a theoretical framework for the relationships between TP and technology acceptance and resistance. In addition, using psychological reactance theory (PRT), research propositions are presented to provide food for thought for future research and to highlight upcoming challenges in the acceptance research of smart products.

Keywords: technology paternalism, smart product, technology resistance, technology acceptance, psychological reactance theory

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The formatting and content of this chapter (e.g., headings, citation style, Table numbers) may slightly differ from the published version.

2.1 Introduction

Smart products have contributed to the disruption of traditional business models, for example, self-driving taxis. Because of the radical innovative character of smart products, there are also new and different aspects influencing consumers' adoption decisions (Raff & Wentzel, 2018). They can act as social agents and affect users on emotional or psychological levels (Shang et al., 2012; van Doorn et al., 2017). Hence, it is necessary to examine the emotional and psychological antecedents that trigger users to accept or reject smart products (Marikyan et al., 2019), as those factors may differ significantly from the postulated factors of traditional acceptance and resistance theories, such as the technology acceptance model (TAM) or unified theory of acceptance and use of technology (UTAUT). For instance, recent research attempts have included new factors like user well-being and happiness (Attié & Meyer-Waarden, 2022; Su et al., 2014; Whillans et al., 2020), trust (Vimalkumar et al., 2021), discomfort and insecurity (Chang & Chen, 2021), and emotions in general (Gerli et al., 2022). In the same vein, some researchers have called to include the effects of autonomy loss resulting from smart product usage (Chi et al., 2020; V. N. Lu et al., 2020; Schein & Rauschnabel, 2021). However, recent publications using classical theories (like TAM or UTAUT) about smart product adoption widely ignore such barriers (e.g., C. Chen et al., 2017; Tu et al., 2022; Yu & Huang, 2020). This may stem from these classical theories lacking the ability to fully grasp emerging technologies like smart products (Shahab et al., 2021).

One of these ignored issues in the use of smart products is technology paternalism (TP). The literature suggests that a technology is paternalistic when an action by this technology directly affects a user, and (1) the user perceives the action as limiting, punishing, or in any other way cutting down on their freedom; (2) they cannot overrule or in any other way disregard the action without sacrificing functionality; (3) the action is claimed to be mainly in the interest of the user; and (4) it is performed by the technology autonomously (Spiekermann & Pallas, 2006). Despite its importance, only a few studies have dealt explicitly with TP and its facets in particular (e.g., Kinder et al., 2008; Spiekermann & Pallas, 2006). A rare exception of empirical work about TP is by Schein and Rauschnabel (2021), who revealed a paternalism factor that was positively correlated with technology resistance and negatively with technology acceptance. In addition, traditional acceptance models make the linear assumption that the more supportive a product is, the higher the perceived usefulness of the product, and therefore, the higher the technology acceptance, which may not be a good representation of the reality of smart products (Chi et al., 2020; Golant, 2017; Marangunić & Granić, 2015). One example is a smart product that provides overly detailed or cumbersome advice, which can lead to the perception of it being paternalistic. Consequently, the assistive action of the smart product may lead to a decrease rather than an increase in perceived usefulness. The author uses the definition of TP as a theoretical framework to show how aspects of TP have already been investigated (intentionally or unintentionally) in several research disciplines. In addition, psychological reactance theory (PRT) is applied as a theoretical lens for proposition development.

In recent research, smart products (Abramovici, 2014) have also been labeled as intelligent products (Raff et al., 2020), smart things (Püschel et al., 2016), smart technologies (Roy et al., 2018), smart systems (Verberne et al., 2012) and smart connected products (Porter & Heppelmann, 2014, 2015). The author considers all these terms similar and defines smart products as devices that are capable of learning, anticipating, and acting independently of user interventions (Raff et al., 2020). They consist of both a digital and a physical part (Abramovici et al., 2016; Pardo et al., 2020), allowing them to link to larger networks (Iansiti & Levien, 2004; Raff et al., 2020), communicate and relate with other smart products or humans (Abramovici et al., 2017; Monostori et al., 2016; Woodside & Sood, 2017), and make decisions about themselves and their interactions with external entities (Sánchez López et al., 2012). Smart products have the ability to learn, act autonomously (de Bellis & Johar, 2020; Rijsdijk et al., 2007), and engage in proactive behavior through predictive analytics (Raff et al., 2020). Due to their ability to exhibit goal-directed behavior, anticipate events, and independently initiate appropriate actions, they are perceived as social agents that can have an emotional and psychological impact on the user (Shang et al., 2012; van Doorn et al., 2017; Wooldridge & Jennings, 1995). An example of a smart product is a smart car. Connected to its environment, it can decide when to slow down, adapt its behavior to its environment, and learn from its network (e.g., about new traffic rules at certain intersections). The definition of smart products also applies to other technologies, such as smart phones.

This study makes several contributions to the literature. First, the topic of TP has been touched upon only in passing and has never been placed in a theoretical context. This paper develops a theoretical framework for the relationship between TP and technology adoption and resistance. Second, the author uses PRT to develop propositions about how the various aspects of TP influence reactance arousal and consequently lead to changes in technology adoption behavior. Third, this is the first attempt to review and structure the body of knowledge from various disciplines about how paternalistic aspects of smart products affect technology acceptance and resistance.

The remainder of this paper is organized as follows. The next section introduces the theoretical framework of this paper, namely the concepts of TP, PRT, and technology acceptance and resistance. The third section provides information on the methodology, the review itself, and the introduction of the framework and thesis of how TP affects technology acceptance and resistance from a PRT perspective. The paper concludes with a discussion of the theoretical and practical contributions, implications for future research, and limitations of the article.

2.2 Theoretical framework

Figure 1 shows the conceptualization of the relationship between perceptions of TP, the arousal of reactance, and the resulting user reactions. For example, users may perceive smart products as paternalistic, which can lead to the arousal of reactance, resulting in user reactions at the psychological and behavioral levels. The relationships outlined in Figure 1 are discussed in more detail in the following sections.

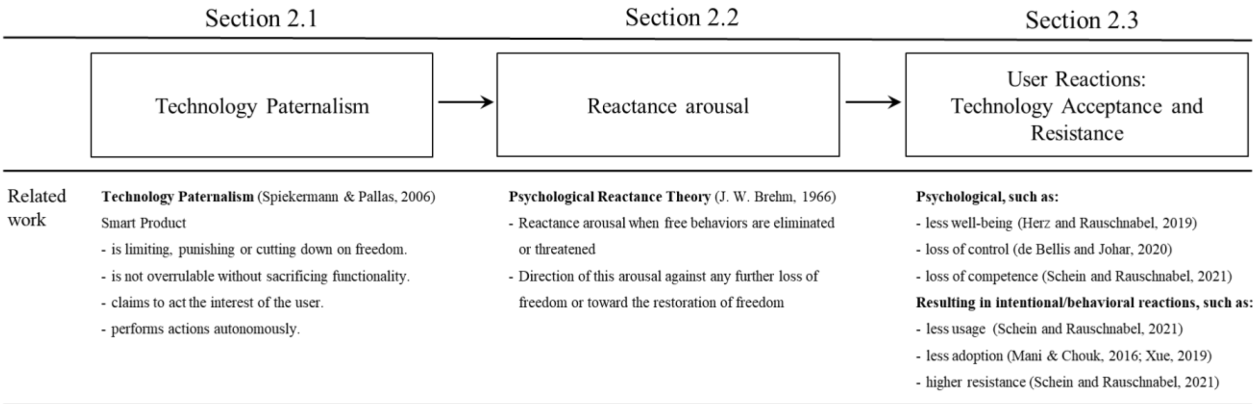


Figure 1: Conceptualization of the relationships between user perceptions of a technology, TP, and user reactions

2.2.1 Technology paternalism

Paternalism is known in social psychology literature as an important area of applied ethics that affects our personal and public lives (Dworkin, 2020). In organizational and sociocultural settings, one can imagine being patronized by a human agent, such as a supervisor, or by a parent in a family setting. Thus, with the advent of artificial intelligence, new potentially paternalistic agents have entered the playing field: smart products as social agents (Shang et al., 2012; van Doorn et al., 2017; Wooldridge & Jennings, 1995). The perception that a smart product has social agency leads it to be perceived as a moral agent worthy of care and concern (Epley & Waytz, 2010). Consequently, "if objects sense what is rightful and what isn't and based on this information limit or castigate peoples' actions, they effectively become paternalistic" (Spiekermann & Pallas, 2006, p. 9).

This leads to the question of what distinguishes paternalistic technology from paternalistic individuals. Smart products act autonomously, leaving little room for individual action and intervention. This highlights the fact "that whilst many of the new technologies are supposed to be 'for our own good' they can end up embodying such extreme levels of automated rule based control that it may become difficult for people to override systems and retain the 'right for the last word" (Kinder et al., 2008, p. 267). As a result, there is a risk that people will no longer be able to override smart products without compromising functionality. Thus, if full functionality is to be ensured, human–technology interaction "is a matter of total compliance" (Spiekermann & Pallas, 2006, p. 10).

TP is a multiplicative model, so all the individual aspects of TP interact to influence the overall perception of TP (Hayes, 2013). These aspects may overlap, and all must be present for TP to be perceived. In a multiplicative model, if one aspect is absent, the result is zero, emphasizing the importance of all aspects in the perception. For example, the action of a smart product cannot be considered paternalistic merely because it is performed autonomously or because it is claimed to be in a person's interest. Smart cars can recognize traffic signs, consider weather forecasts, analyze the driver's current driving style, and slow down – even against the driver's will – because accident statistics show a high risk of accidents in the area being approached. Applying the above definition of TP, one action is evident that restricts the user's freedom (slowing down the car against the user's will). This action is performed autonomously and cannot be overridden without losing functionality (if the driver takes control, they sacrifice the functionality of autonomous driving). It is also claimed that slowing down the vehicle is for the driver's own good. Accordingly, paternalistic technologies can influence resistance to and acceptance of the technology.

2.2.2 Psychological reactance theory

To understand how TP affects resistance to and acceptance of smart products, it is necessary to theorize how and why people respond to threats based on TP as they are. Besides PRT, other related theories such as self-determination theory (Deci & Ryan, 2012) may be appropriate for this purpose. Nevertheless, according to Occam's razor (Duignan, 2023), the author chose PRT, prioritizing simplicity by utilizing the simplest explanation of an entity.

PRT posits that when something threatens or eliminates behavioral freedom, people experience psychological reactance (J. W. Brehm, 1966). The theory includes four key elements: freedom, threat to freedom, arousal to reactance, and restoration of freedom. Freedom is defined as "a set of behaviors, any one of which a person could engage in either at the moment or at some time in the future" (J. W. Brehm, 1966, p. 3), which includes actions as well as emotions and attitudes. A threat to freedom is any force on the individual that increases the difficulty of exercising freedom. The arousal of reactance occurs when individuals feel that their free behaviors are being eliminated or threatened (Miron & Brehm, 2006). This can be any circumstance that prevents individuals from exercising their freedom and can take any form, such as prohibition (e.g., the smart car forbids speeding) or persuasion (e.g., the smart car recommends taking a break).

As a result, consumers are motivationally aroused and direct this arousal against any further loss of freedom or toward the restoration of freedom (J. W. Brehm, 1966). Reactance depends in part on the individual, for example, the individual's awareness of the threatened behavior (S. S. Brehm & Brehm, 1981; Miron & Brehm, 2006), the importance attached to that behavior (J. W. Brehm, 1966), the individual's perception of their ability to restore the threatened freedom (Kray et al., 2004; Wright et al., 2015), or the perceived degree to which their free behaviors are threatened (J. W. Brehm, 1966; Miron & Brehm, 2006). The arousal of reactance leads to less positive evaluations of paternalistic products (Roubroeks et al., 2010). Consumers who value privacy resist website personalization (Brinson et al., 2018; Ham, 2017), while those who value manual labor meaning prefer traditional over autonomous products (de Bellis et al., 2023). This suggests that "too much" advice, support, or autonomous action from a smart product may be perceived as "bad" or a threat to freedom. However, some previous research suggests that "more advice and support from technologies is always better" (e.g., TAM (Davis, 1989) or UTAUT (Venkatesh et al., 2003); Guha et al. (2022), for example, propose a linear positive relationship between voice assistant intelligence and user ratings).

2.2.3 Technology acceptance and resistance

The arousal of reactance results in a change in technology acceptance or resistance. Technology acceptance is an individual's intentional or voluntary use of a technology (Davis, 1989). One of the most used frameworks for studying technology acceptance is Davis' (1989) TAM, which indicates two main factors that influence individuals' acceptance of technology: perceived ease of use and perceived usefulness. TAM is parsimonious and robust (Chuttur, 2009) and has had fundamental implications for understanding how individuals adopt technology. For example, recent smart product-specific research has shown that higher perceived ease of use positively influences the adoption of AI systems in agriculture (Mohr & Kühl, 2021), and that perceived usefulness positively influences customers' intentions to use a technology (Roy et al., 2018; Yu & Huang, 2020). However, there are concerns with TAM, such as the lack of acceptance barriers within the model (Rauschnabel et al., 2018).

Another concept that plays an important role in how smart products are rejected is technology resistance. Technology resistance can be defined as "a person's proactive intention to resist using a technology" (Schein & Rauschnabel, 2021, p. 3). In contrast to acceptance research, technology resistance research assumes that technologies have disadvantages as well as benefits (Markus, 1983; Saga & Zmud, 1993). For example, in a TP context, a smart product may make a user's task more efficient, but the user perceives the technology as paternalistic, leading to their avoidance of the technology because they perceive it as a threat, even though it makes their job easier. Factors influencing technology resistance may include fear and stress (Marakas & Hornik, 1996); fear of receiving false, inappropriate, or excessive information (Schein & Rauschnabel, 2021); perceived loss of power or status (Lapointe & Rivard, 2005; Smith & McKeen, 1992); perceived disruption of internal causal attributions (Martinko et al., 1996); loss of job security (Schein & Rauschnabel, 2021); fear of surveillance (Rauschnabel et al., 2018; Schein & Rauschnabel, 2021); decreased well-being (Herz &

Rauschnabel, 2019); decreased user experience and happiness (Whillans et al., 2020); or loss of competence (Joshi, 1991; Spreer & Rauschnabel, 2016).

2.3 Literature review: Aspects of technology paternalism from a reactance theory perspective

The relationship between TP and technology resistance and acceptance has been studied (intentionally or unintentionally) in various fields, such as human–computer interaction, management, marketing, and information systems. This manuscript aims to bring together all available information on this phenomenon from different research fields and to analyze the literature based on the definition of TP.

2.3.1 Methodology

This review uses a semi-systematic approach to synthesize existing knowledge and formulate a research agenda using meta-narratives. This approach is designed for topics that have been conceptualized and studied in different ways and disciplines (Snyder, 2019). The detection of themes, theoretical perspectives, or prevalent concerns within a research discipline, or the identification of components of a theoretical concept, can be facilitated through this approach (Ward et al., 2009). Following Webster and Watson (2002), relevant literature was collected using predefined search parameters in various databases. A forward and backward citation search was also used to ensure a comprehensive review of the relevant literature (Tranfield et al., 2003; Webster & Watson, 2002). The databases, search terms, and inclusion criteria used are listed in Table 2, resulting in an initial list of 228 titles for further review.

Table 2: Search terms and inclusion criteria (both American English and British English were considered)

Boolean search term(s)	-	"technology" AND "paternalism" OR "patronization"
	-	"cyber paternalism" OR "nudging technology" OR "techno paternalism"
	-	"technological paternalism"
Publication dates		2005–2021
Language of publications		English
Types of publication	-	Peer-reviewed journals and books
	-	Books by well-known editors/publishers
	-	Conference proceedings and papers
Databases	-	JSTOR
	-	Scopus
	-	Business Source Premier
	-	Google Scholar[3]
	-	ScienceDirect

[3]According to Gusenbauer (2019), Google Scholar is currently the most comprehensive academic search engine.

The approach to selecting articles followed Snyder (2019), and resulted in 21 remaining titles. The thematic fit of each article was considered essential in the evaluation, and articles focused on specific technical aspects were excluded. Studies limited to a specific product or product group were also considered, as the overall literature in this area is limited. Additional articles were identified through forward and backward cross-referenced searches in two successive waves. Wave one resulted in 43 additional publications, and wave two (based on the additional articles in wave one) resulted in 46 additional articles. The final 110 articles were read and re-evaluated for content. No further narrowing of the sample was done to avoid compromising the depth and rigor of the literature study (Snyder, 2019). A schema was created to include descriptive data, content summaries, and other notes (including research stream, number of citations, and theories used). An overview of the literature screening process is provided in Figure 2. Table 32 in the appendix offers a complete list of all publications taken into account.

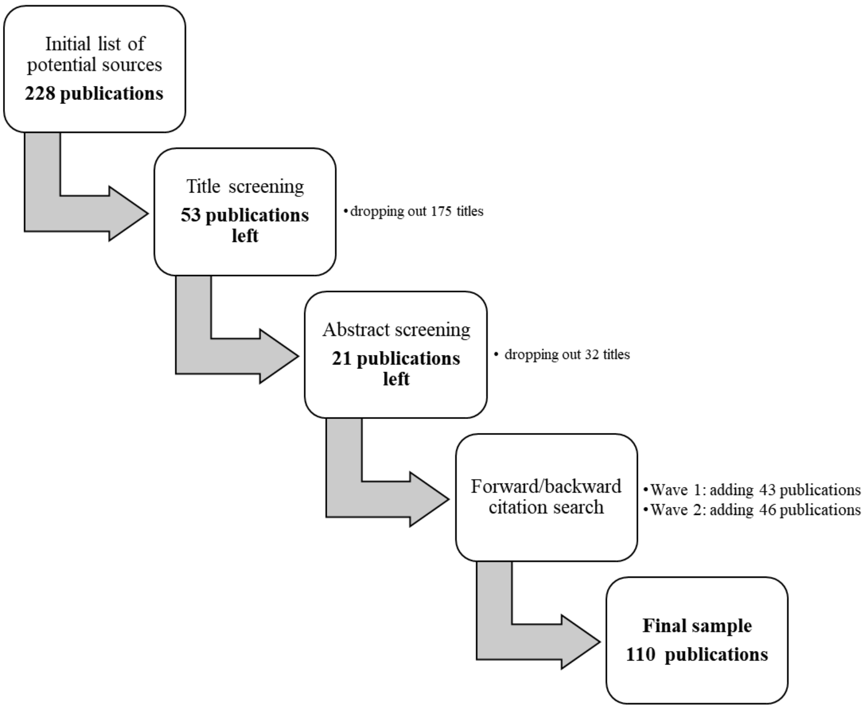


Figure 2: The literature screening process

After finalizing the sample, the author created a concept matrix based on the definition of TP and its dimensions. The literature was then analyzed to determine the coverage of aspects of TP, such as the effects of autonomous machine actions on user perception or the effects of (unsolicited) advice by technologies (among others). In addition, possible moderating effects discussed in the literature were considered.

2.3.2 Technology paternalism in a psychological reactance theory context

This section summarizes the extent to which the aspects of TP have been analyzed in the literature and presents propositions. All four boundaries are considered to be interrelated (see 2.1). This means that aspects of TP can affect more than one dimension.

Limiting User Freedom: How Smart Products Threat User Freedom

According to Spiekermann and Pallas (2006), for technology to be considered paternalistic, its actions must be perceived as restricting, punishing, or otherwise limiting freedom. From the perspective of PRT (J. W. Brehm, 1966), this restriction of freedom is perceived as a threat to behavior, which leads to an attempt to restore freedom, which may manifest itself in altered product acceptance behavior. For example, if a smart car slows down against the user's will, the user may feel that their autonomy is threatened. If the user can override the decision, they may do so. However, if the user is unable to override the decision, for example, because it would require deep programming knowledge or because the default settings do not allow it, this may lead to a change in the attractiveness of the threatened behavior and the available alternatives. This may include engaging in a behavior that is somehow equivalent to the threatened or eliminated behavior, such as purchasing a different autonomous car that can be overridden, having a peer engage in the threatened behavior, or aggressing toward the source of the threat (Dickenberger & Gniech, 2019).

When smart products do not inform users of decisions or provide sufficient opportunities for interruption, it leads to a perception of loss of autonomy and control (Mani & Chouk, 2017; Rödel et al., 2014; Xue, 2019), which can reduce product adoption (Boeck et al., 2011; Buchanan et al., 2016; Pollak et al., 2020; Rijsdijk & Hultink, 2009; F. Schweitzer & van den Hende, 2016). The more autonomous a product becomes, the more it may lead to a decrease in adoption intentions (Souka et al., 2020), as consumers are reluctant to give up control over certain features (König & Neumayr, 2017; Nikolaidis et al., 2015; Souka et al., 2020) and may perceive autonomous machines as threatening (Złotowski et al., 2017) and more intrusive than their non-autonomous counterparts (Gaudiello et al., 2016; Raff & Wentzel, 2018). This is also true in other settings, such as smart homes (T. Hargreaves & Wilson, 2017; Sovacool et al., 2020; Wilson et al., 2017).

When users are denied the opportunity to customize or intervene in the decision-making process of smart products, it leads to decreased trust (Dietvorst & Bharti, 2020; Sharan & Romano, 2020) and a lack of perceived agency over outcomes (Dietvorst et al., 2018; N. Wang et al., 2018). This can lead to a "servant-master relationship" in which the user must follow the rules of the technology to ensure full functionality (F. Schweitzer et al., 2019, p. 9). In addition, higher levels of technological support may reduce feelings of agency (Coyle et al., 2012). To counteract these negative effects, it is important to provide users with sufficient control and opportunities for intervention and customization, and to involve them in the decision-making process (Ehrenhard et al., 2014; Mani & Chouk, 2019; Milchram et al., 2018; Moser, 2017; E. Park et al., 2018; F. Schweitzer & van den Hende, 2016; Stein et al., 2019; N. Wang et al., 2018).

In summary, the lack of user customization, the ability of smart products to act without the user's consent, and the removal of the user from the decision-making process all lead to a perceived threat to freedom. However, only when users perceive this threat to their personal freedom will they perceive the technology as paternalistic and consequently develop a psychological reactance that leads to an adjustment of attitudes toward the product. To restore freedom and reduce reactance, certain subjective or behavioral responses occur, such as reduced acceptance of the technology.

Proposition 1: To be perceived as paternalistic, a smart product must be perceived as a threat to freedom, at least to some extent. This leads to the arousal of reactance.

Lack of Overruling Prospects: How Overruling Opportunities for Users Affect Technology Acceptance

A technology acts paternalistically when its decisions cannot be overridden by the user without compromising its functionality (Spiekermann & Pallas, 2006). When certain features or functions cannot be easily turned off, the user is placed in a paternalistic relationship with the device. When laws, regulations, and other rules are embedded in the software code and cannot be negotiated or ignored, the user is in a position of being controlled by the technology (Millar, 2015; Sørensen & Schmidt, 2016).

In most cases, smart products are unable to perfectly understand and adapt to users' detailed requests and contexts because these "AI-enabled services tend to be highly structured with the sequence of steps a customer has to go through often determined by the requirements of the technology rather than the needs of the user" (Ameen et al., 2021, p. 4). As a result, these technologies are often structured in a way that prioritizes the requirements of the technology over the needs of the user, meaning that people often perceive smart products' algorithms as lacking flexibility and context sensitivity (Langer & Landers, 2021; Newman et al., 2020). This problem can arise in a variety of settings, such as in a work environment where conditions may change and users may need to modify workflows that deviate from the instructions of the smart product. Users may develop ways to circumvent or cheat the technology to avoid unwanted actions or penalties (Kinder et al., 2008; Lawrence, 2006; Wong et al., 2022). This behavior can be interpreted as an attempt to regain threatened freedom and reduce reactance. To address this problem, it is important to leave some room for users to adapt processes according to changing conditions (Dietvorst et al., 2018; Meissner et al., 2020; Schein & Rauschnabel, 2021; R. Yang & Newman, 2013) and to incorporate user opinions into smart product decision processes (Köbis & Mossink, 2021).

In summary, in most cases, it is not possible to override smart products without loss of functionality without expert knowledge. A lack of adaptability and flexibility leads to a paternalistic relationship between the user and the technology, which forces the user to circumvent the technology to outsmart it and regain personal freedom if possible. This TP threatens individual freedom and therefore affects the psychological response. Thus, the arousal of reactance influences technology acceptance.

Proposition 2: To be perceived as paternalistic, a smart product must not be able to be overwritten without functionality loss. This leads to an arousal of reactance.

Acting Autonomous: How Autonomous Actions of Technologies Affect User Acceptance

A technology must act autonomously to be perceived as paternalistic (Spiekermann & Pallas, 2006). Companies collect and process large amounts of personal data and contextual information to provide smart products and services that are more adaptable to the user and the context of use (Henkens et al., 2021). However, these processes often occur without the customer's knowledge or consent, which can lead to feelings of threatened autonomy (N. Wang et al., 2018; Yost et al., 2019). Additionally, if the smart product makes changes without the user's input, it can lead to confusion and feelings of incompetence, which may cause the user to avoid using the product (Rijsdijk & Hultink, 2009). Furthermore, autonomously acting smart products can deprive consumers of meaningful experiences. For instance, some consumers derive meaning from performing manual tasks, while autonomous acting products remove that source of meaning (de Bellis et al., 2023).

When users are not informed about the reasoning behind the decisions made by technology, they tend to experience greater reactance and a lower sense of autonomy (Brell et al., 2019), especially when the data involved is identity sensitive, such as on social networks (Rader & Gray, 2015; Sankaran et al., 2021) or when privacy is highly valued (X. Chen et al., 2021). In addition, people are more likely to hesitate if they do not understand how a smart product's algorithm works or how it arrives at a decision (Dzindolet et al., 2002; Kayande et al., 2009). This underscores the importance of transparent decision-making processes and user consent, which can help consumers anticipate or prevent decisions made by technology. Michler et al. (2020, p. 399) state, that "the process by which a smart product makes decisions should also be transparent; this includes the way a smart product interprets existing data and comes to a decision using its algorithms." Providing users with ongoing information about what the smart product is doing and the current confidence level of the autonomous system can reduce customers' perceptions of threat (Antifakos et al., 2005; Ekman et al., 2018; Josten et al., 2017; Rijsdijk & Hultink, 2009). Therefore, smart products can benefit from making their algorithms more transparent (Hardian et al., 2006; Litterscheidt & Streich, 2020; Sharan & Romano, 2020) and ensuring that the goals of the technology are aligned with those of the user (Roubroeks et al., 2010).

In summary, smart products use pervasive and hidden processes to adapt to the user and the context without the user's consent. This is likely to lead to a perceived threat to autonomy and consequently, to the arousal of reactance. Greater transparency in decision making could help users predict outcomes and understand the rationale for the smart product. This would lead to a lower perceived threat to freedom and less reactance.

Proposition 3: To be perceived as paternalistic, a smart product must act autonomously and without the user's consent. This leads to an arousal of reactance.

Welfare Intention: How Honorable Reasons Moderate Technology Acceptance and Resistance

Paternalistic actions by technologies presuppose good intentions (Spiekermann & Pallas, 2006). In addition to improving the well-being of the user (e.g., reducing human workload by increasing efficiency), technology can also consider how the user's actions may affect others (Dworkin, 2020). An example of this is intelligent assistants and recommendation systems, which are designed to increase people's well-being by reducing search time and costs. For instance, a smart car may provide users with information about restaurants nearby to save searching time. These intentions may be seen as noble, but could also undermine individual decision-making processes (Appelgren, 2018, 2019; Helbing et al., 2019) and may lead to a perceived restriction of personal freedom or a threat to future behavior, which in turn can reduce the intention to use the technology (G. Lee & Lee, 2009; Weiser et al., 2016).

People generally prefer detailed explanations with more information (Gönül et al., 2006). However, it is not always true that the more information a smart product provides, the more helpful it is. Beyond a certain point, too much transparency and overly detailed explanations and justifications can undermine trust in the technology (Kizilcec, 2016), frustrate the user (Glass et al., 2008), be perceived as confusing and complicated (Kulesza et al., 2013), cause information overload (Barria-Pineda et al., 2019; Bunt et al., 2012; B. Y. Lim & Dey, 2009; Millecamp et al., 2019; Schein & Rauschnabel, 2021; Wiebe et al., 2016), or lead to discomfort and decreased intentions to use it (Swar et al., 2017). As a result, the perceived costs of using the technology can outweigh the expected benefits due to an overwhelming amount of information (Bunt et al., 2012). Overly detailed explanations can negatively impact users' ability to identify errors in the recommendations themselves (Poursabzi-Sangdeh et al., 2021) and result in increased user response time (Narayanan et al., 2018).

Research by van Swol et al. (2017), Aguirre et al. (2015) and Gino (2008) also showed that unsolicited advice is valued less than voluntary and requested advice. This is also true for smart products, where unsolicited advice can lead consumers to ignore technology recommendations and trigger boomerang effects (doing the opposite of what is recommended) (Feng & Magen, 2016; Fitzsimons & Lehmann, 2004; G. Lee & Lee, 2009; Murray & Häubl, 2009). On the other hand, people who have invested money, time, and effort in obtaining information are less likely to ignore it (Sutherland et al., 2016).

In summary, the balance between transparency and support in smart products is important for acceptance. Too little transparency can lead to mistrust, while too much support can lead to information overload. Finding the right balance is critical for maximizing the perceived usefulness of the technology. As more support is provided, the perceived usefulness initially increases but eventually peaks and begins to decline, creating an inverted U-shaped effect. In addition, information seeking influences the perception of support from smart products.

Proposition 4a: The effects of P1–P3 are moderated by the amount of information provided by the smart product. This effect follows an inverted U-shaped function.

Proposition 4b: The effects of P1–P3 are moderated by information solicitation. If the smart product provides information that is unsolicited/solicited, the moderation effect is higher/lower.

Further Potential Moderators of Technology Paternalism

The effectiveness of the aforementioned propositions can be influenced by various factors, such as allowing users to customize the workflow (Royakkers & van Est, 2015; N. Wang et al., 2018; Wieland et al., 2009), providing opt-out options for certain features (Brell et al., 2019; Hock et al., 2019; Millar, 2015; Royakkers & van Est, 2015), providing transparent feedback (Ehrenbrink et al., 2016), and aligning the system with the user's goals (Ekman et al., 2018). Furthermore, implementing shared goals between the user and the product can also improve the effectiveness of the technology (e.g., in the context of a smart car: sporty vs. ecological driving) (Roubroeks et al., 2010).

In this sense, designing interfaces that provide users with the ability to regain control when needed can reduce distrust, fear of dysfunction, and feelings of helplessness (Brell et al., 2019; Cronin, 2010; Glass et al., 2008; T. Hargreaves & Wilson, 2017; Link et al., 2013; F. Schweitzer & van den Hende, 2016); increase perceived self-control (Milchram et al., 2018); and reduce perceived disempowerment (de Bellis & Johar, 2020). A balance between standard personalization and user-controlled personalization is necessary, and depends on individual needs, characteristics, and context of use and expertise (Glass et al., 2008; Hardian et al., 2006; Logg et al., 2019; N. Wang et al., 2018). Personalization and customization features also increase user trust in smart products (Ghazali et al., 2018a).

Proposition 5: The effects of P1–P3 are moderated by the adaptability of a smart product.

Anthropomorphic design of smart products may also influence technology acceptance (Qiu & Benbasat, 2009; L. Zhang et al., 2021) or how we feel about using them (Whillans et al., 2020). Products designed with friendly features (e.g., "friendly eyebrow gestures") are more persuasive and elicit less psychological reactance than products with human facial features, which are typically considered untrustworthy (Ghazali et al., 2018a). Threatening language from smart products leads to greater arousal of reactance (Roubroeks et al., 2010), especially when they lack social cues (Ghazali et al., 2017, 2018b, 2019; Roubroeks et al., 2009). Human-like appearance (Waytz et al., 2014; Złotowski et al., 2015), the ability to read human emotions (M.-H. Huang & Rust, 2018), and social-emotional capabilities (Wirtz et al., 2018) also promote the adoption of smart products. Furthermore, the ability to customize and individualize human-like features of a technology increases acceptance (Broadbent et al., 2009) and leads to higher adoption of its recommendations (Hanus & Fox, 2017).

Proposition 6: The effects of P1–P3 are moderated by the anthropomorphism of a smart product.

According to Miron and Brehm (2006), the degree of reactance experienced in response to a perceived threat to freedom depends on an individual's ability or willingness to restore that freedom and the perceived difficulty of doing so. When an individual's motivation to restore freedom is held constant, the degree of reactance is a cubic function of the complexity of restoring that freedom (Miron & Brehm, 2006). If the individual has no idea how difficult it will be to restore the threatened freedom (e.g., if they do not know how difficult it will be to overcome a paternalistic technology), they will exert as much effort as they think is worthwhile to restore the threatened freedom. If the individual believes that it will be easy to restore the threatened freedom (e.g., because they know that it is easy to overcome a paternalistic technology), they will exhibit limited reactance, and the expected effort to restore freedom will be relative to the perceived difficulty of restoring it. The more difficult it is to restore the freedom threatened by the paternalistic technology, the greater the reactance (see Figure 3).

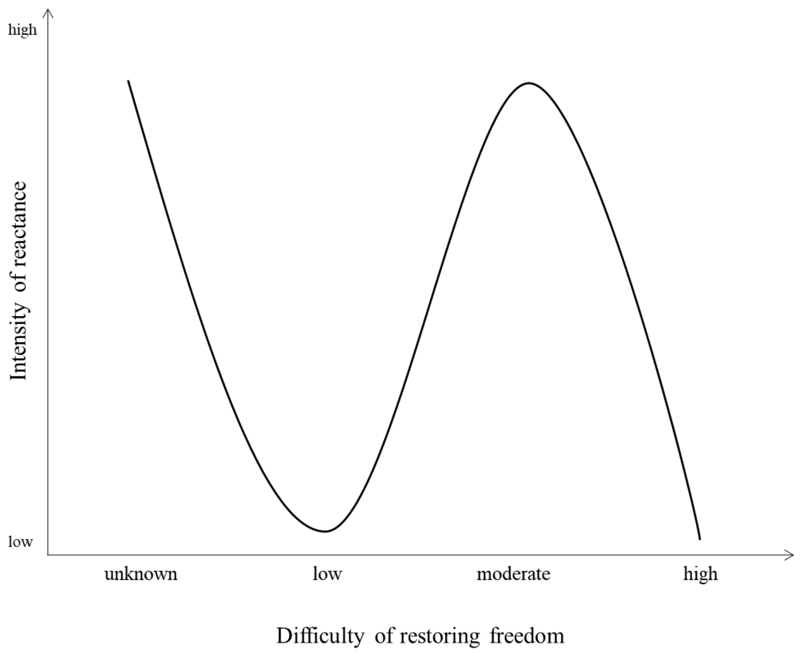


Figure 3: Intensity of reactance as a cubic function of difficulty restoring freedom (adapted from Miron & Brehm, 2006)

Thus, when a perceived threat to freedom is moderately difficult to restore, it leads to high reactance motivation, and the individual will take action to restore the freedom (e.g., yelling fervently at the paternalistic technology or trying to overcome or outsmart the technology). However, when the individual realizes that restoring freedom is impossible (e.g., when they realize that all efforts to outsmart the technology are futile), the reactance motivation decreases or becomes zero, and the individual accepts the technology's decision (Mikulincer, 1988; Tracey et al., 1989).

Task and interaction experience may also play a role. People with less experience using smart products may perceive tasks as more difficult and show higher levels of reactance. J. S. Lim and O'Connor (1996) found that people who were unfamiliar with smart products' algorithms showed higher levels of aversion. This may also be relevant to experience with (and thus mastery of) smart products. It explains why experienced workers perceive smart product support as more paternalistic than novice workers (R. Yang & Newman, 2013). Novice workers conclude that it is very difficult to regain their freedom, and thus show little or no responsiveness, while experienced users may see opportunities to regain threatened freedom and show more reactivity, or (conversely) have accepted that the technology cannot be overcome and show less reactance. Novice users may experience higher levels of reactance when they first encounter paternalistic technology, but as they gain experience, their reactance arousal may decrease.

Proposition 7a: The effects of P1–P3 are moderated by the degree of the user's relevant task experience.

Proposition 7b: The effects of P1–P3 are moderated by the degree of the user's experience in handling smart products.

Table 3 and Figure 4 below summarize the developed propositions.

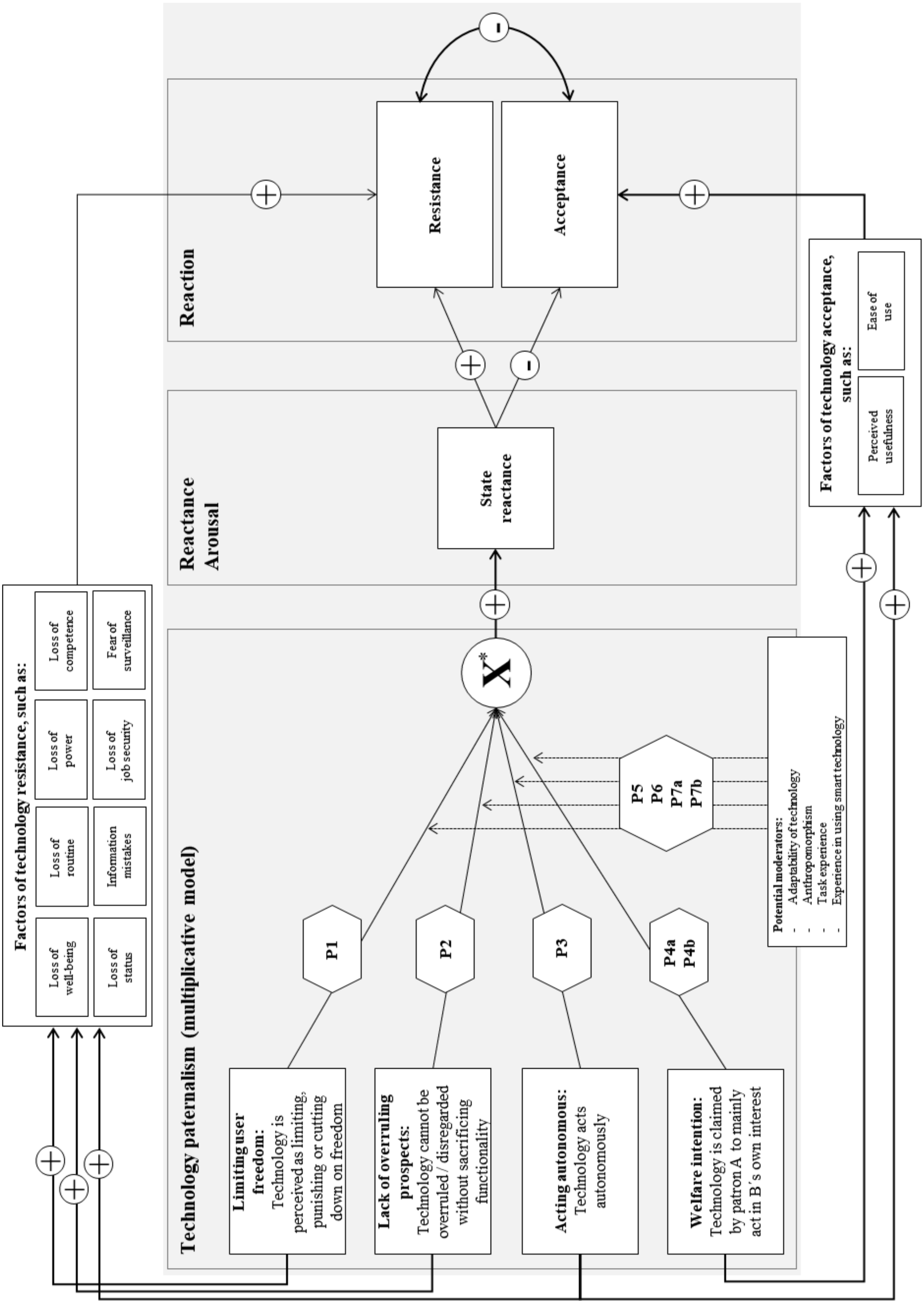
Table 3: Technology paternalism: propositions and potential moderators

Proposition	Aspect of TP	Link to PRT	Example – Smart car	Sources*
Proposition 1: To be perceived as paternalistic, a smart product must be perceived as a threat to freedom, at least to some extent. This leads to the arousal of reactance.	**Limiting user freedom:** Technology actions are perceived as limiting, punishing, or in any way cutting down on freedom.	By restricting the user's freedom, smart products threaten the individual's free behavior, leading to the arousal of reactance.	Based on information about a high-risk section of road ahead, an autonomous car slows down against the user/driver's will. The driver perceives this as a threat to their freedom, which leads to the arousal of reactance. To regain freedom, one can increase the attractiveness of the threatened freedom, engage in a behavior that is somehow equivalent to the threatened behavior, get a peer to engage in the threatened behavior, or aggress toward the source of the threat.	Spiekermann and Pallas (2006); Rijsdijk and Hultink (2009); Boeck et al. (2011); Coyle et al. (2012); Ehrenhard et al. (2014); Rödel et al. (2014); Nikolaidis et al. (2015); Buchanan et al. (2016); Gaudiello et al. (2016); Mani and Chouk (2017); F. Schweitzer and van den Hende (2016); Hargreaves and Wilson (2017); König and Neumayr (2017); Moser (2017); N. Wang et al. (2018); Wilson et al. (2017); Złotowski et al. (2017); Dietvorst et al. (2018); Milchram et al. (2018); E. Park et al. (2018); Dickenberger and Gniech (2019); Mani and Chouk (2019); Raff and Wentzel (2018); F. Schweitzer et al. (2019); Stein et al. (2019); Xue (2019); Dietvorst and Bharti (2020); Pollak et al. (2020); Sharan and Romano (2020); Souka et al. (2020); Sovacool et al. (2020);
Proposition 2: To be perceived as paternalistic, a smart product must not be able to be overwritten without functionality loss. This leads to an arousal of reactance.	**Lack of overruling prospects:** The decisions and actions of the technology cannot be overruled without sacrificing functionality.	By limiting the ability to override, smart products threaten the free behavior of individuals, which leads to the arousal of reactance.	If the smart car cannot be overridden without sacrificing functionality (e.g., losing autonomous product attributes), this leads to a decrease in perceived freedom and thus to an arousal of reactance.	Lawrence (2006); Spiekermann and Pallas (2006); Kinder et al. (2008); R. Yang and Newman (2013); Behmann and Wu (2015); Millar (2015); Sørensen and Schmidt (2016); Dietvorst et al. (2018); Michler et al. (2020); Newman et al. (2020); Meissner et al. (2020); Ameen et al. (2021); Langer and Landers (2021); Schein and Rauschnabel (2021); Köbis and Mossink (2021); Wong et al. (2022)
Proposition 3: To be perceived as paternalistic, a smart product must act autonomously and without the user's consent. This leads to an arousal of reactance.	**Acting autonomous:** The technology must perform autonomously.	By acting autonomously, smart products threaten the free behavior of individuals, leading to the arousal of reactance.	The smart car dynamically makes ongoing changes (e.g., due to changing weather conditions). Users may be confused by these changes (e.g., because the car has changed the route) or perceive complexity. This leads to perceived threats to autonomy and increased reactivity.	Dzindolet et al. (2002); Antifakos et al. (2005); Hardian et al. (2006); Spiekermann and Pallas (2006);Kayande et al. (2009); Rijsdijk and Hultink (2009); M. A. J. Roubroeks et al. (2010); Rader and Gray (2015); Ehrenbrink et al. (2016); Josten et al. (2017); N. Wang et al. (2018); Ekman et al. (2018); Brell et al. (2019); Yost et al. (2019); Litterscheidt and Streich (2020); Michler et al. (2020); Sharan and Romano (2020); X. Chen et al. (2021); Henkens et al. (2021); Sankaran et al. (2021)
Proposition 4a: The effects of P1–P3 are moderated by the amount of information provided by the smart product. This effect follows an inverted U-shaped function. **Proposition 4b:** The effects of P1–P3 are moderated by information solicitation. If the smart product provides information that is unsolicited/solicited, the moderation effect is higher/lower.	**Welfare intention:** The technology's actions are claimed by patron A to be mainly in the users' interests.	Honorable reasons for autonomous actions of smart products can lead to perceived paternalism, which threatens the free behavior of individuals and leads to the arousal of reactance.	The smart car provides detailed information about the current status of the system, which can be perceived as intrusive and overly detailed. This leads to a perceived threat to freedom and therefore increases reactance. If the smart car provides detailed information or advice (such as changing the route or driving style due to icy, slippery roads in winter) without prompting, this may be perceived as a threat to freedom and therefore increase reactance arousal.	Fitzsimons and Lehmann (2004); Gönül et al. (2006); Spiekermann and Pallas (2006); Gino (2008); Glass et al. (2008); G. Lee and Lee (2009); B. Y. Lim and Dey (2009); Murray and Häubl (2009); Bunt et al. (2012); Kulesza et al. (2013); Aguirre et al. (2015); Kulesza et al. (2015); Feng and Magen (2016); Kizilcec (2016); Sutherland et al. (2016); Weiser et al. (2016); Wiebe et al. (2016); Swar et al. (2017); van Swol et al. (2017); (Appelgren, 2018); Helbing et al. (2019); Narayanan et al. (2018); Appelgren (2019); Barria-Pineda et al. (2019); Dworkin (2020); Millecamp et al. (2019); Michler et al. (2020); Poursabzi-Sangdeh et al. (2021); Schein and Rauschnabel (2021)

Proposition 5: The effects of P1–P3 are moderated by the adaptability of a smart product.	Potential moderator	An increase in customization options increases perceptions of identity with the source and control over the source, which reduces psychological reactance.	If a smart car offers adaptive options, such as changing the amount of information provided or adjusting shared goals, this may lead to less paternalistic effects and thus reduce the arousal of reactance.	Hardian et al. (2006); Glass et al. (2008); Wieland et al. (2009); Cronin (2010); M. A. J. Roubroeks et al. (2010); Link et al. (2013); Millar (2015); Royakkers and van Est (2015); Ehrenbrink et al. (2016); F. Schweitzer and van den Hende (2016); Hargreaves and Wilson (2017); N. Wang et al. (2018); Ekman et al. (2018); Ghazali et al. (2018a); Milchram et al. (2018); Brell et al. (2019); Hock et al. (2019); Logg et al. (2019); de Bellis and Johar (2020)
Proposition 6: The effects of P1–P3 are moderated by the anthropomorphism of a smart product.	Potential moderator	Anthropomorphizing products makes them more persuasive and reduces psychological reactance.	When a smart car offers customization options according to its anthropomorphic look and feel, the negative effects of its paternalistic characteristics are reduced.	Broadbent et al. (2009); Qiu and Benbasat (2009); M. Roubroeks et al. (2009); M. A. J. Roubroeks et al. (2010); Waytz et al. (2014); Złotowski et al. (2015); Ghazali et al. (2017); Hanus and Fox (2017); Huang and Rust (2018); Wirtz et al. (2018); Ghazali et al. (2018a); Ghazali et al. (2018b); Ghazali et al. (2019); L. Zhang et al. (2021)
Proposition 7a: The effects of P1–P3 are moderated by the degree of the user's relevant task experience. **Proposition 7b**: The effects of P1–P3 are moderated by the degree of the user's experience in handling smart products.	Potential moderator	Motivational arousal to achieve or avoid an outcome is a function of how capable or willing a person is to achieve or avoid that outcome and the perceived difficulty of performing the instrumental behavior carried out to achieve the goal.	Drivers with little to no driving experience perceive the driving task as more complex and are therefore more open to support. Therefore, they do not develop reactance. This effect is reversed for experienced drivers. Drivers with no experience in using and adapting smart technologies (e.g., by changing the code) show less or no reactance to paternalistic features of the car because they perceive the restoration of the threatened freedom as unreachable. Thus, they do not develop reactance because they do not believe they can change the situation. This effect is reversed for users with prior knowledge of programming or the use of intelligent technology.	Mikulincer (1988); Tracey et al. (1989); J. S. Lim and O'Connor (1996); Miron and Brehm (2006); R. Yang and Newman (2013)

* = Most of the sources are not from TP research but are drawn from other research disciplines; no claim for completeness

Figure 4: Conceptual framework of technology paternalism in a PRT context



** = "x" represents the multiplicative character of the definition of TP*

2.4 Discussion

Although smart products will play a major role in almost everyone's life in the next decade, relatively little is known about TP. Although it was introduced by Spiekermann and Pallas in 2006, the author is not aware of any paper that examines TP in detail. Thus, the first goal of this paper was to explore how TP may affect users who interact with smart products. While some aspects of TP, such as perceived autonomy compromised by autonomously acting smart products, may be relatively obvious, other effects may not be as clear, for example, the negative effects of excessive user support.

The common assumption in technology adoption research of "the more support, the better" no longer holds. Our review shows that product smartness has both positive and negative effects on adoption. Nevertheless, in recent years, scholars have not emphasized TP as an influencing aspect. Thus, the second objective of this paper was to explore the dynamics through which TP may have an impact on product adoption or resistance. The author developed a model, shown in Figure 4, which demonstrates that TP and its dimensions have direct and indirect effects on technology acceptance and resistance. On one hand, welfare intention and product autonomy may have a direct impact on perceived usefulness or ease of use. On the other hand, if too much support leads to TP, the autonomy and welfare intention of the product may have an indirect effect on technology acceptance and resistance, as it may lead to the arousal of reactance. Limiting user autonomy and offering limited override options can lead to direct effects such as loss of control or sense of agency and can increase perceived TP and lead to higher reactance.

The multiplicative nature of TP has several implications. First, paternalistic features of smart products may be complementary and even mutually reinforce perceived TP. Second, TP develops only when all four of its dimensions are perceived. For instance, if a product is perceived as reducing freedom but does not have any of the other three dimensions, it is not perceived as paternalistic.

2.4.1 Theoretical contributions

This study makes several important contributions that could benefit researchers. First, the author notes that TP has not received the scholarly attention it deserves. To date, it has only been conceptualized (Spiekermann & Pallas, 2006) or briefly touched upon by research attempts such as Kinder et al. (2008), Millar (2015) or Hilty (2015). Quantitative research approaches are even rarer; to the best of the authors' knowledge, only

Schein and Rauschnabel (2021) have empirically demonstrated the existence of a TP effect. The introduced model of TP contributes to the limited literature on TP by identifying the dimensions of TP and its multiplicative characteristics. The model adds knowledge to the well-developed literature on technology acceptance and resistance by introducing a new influencing factor on how smart products may be perceived.

Second, the concept of TP enriches our understanding of what characteristics of smart products can generate negative associations in users. Because researchers have largely focused on linear associations of amplified benefits from smart products and the resulting intent to use rather than the potentially negative aspects, it is likely that the focus on amplifying the capabilities of smart products actually intensifies negative influences as well. This raises the interesting question of which of the four dimensions of TP has the most influence, and importantly for future theory building, under what conditions.

Third, the proposed model contributes to the literature on acceptance and resistance to smart products by clarifying how the four dimensions of TP interact, cause reactance, and ultimately directly and indirectly influence product adoption. The representation of TP in terms of four dimensions also clarifies the conditions under which individual users evaluate paternalistic aspects of products.

2.4.2 Managerial implications

This study has several practical implications for smart product developers and managers. First, smart product developers should consider TP as an influential factor in technology resistance and acceptance. The review provides an initial understanding of the effects that may occur when users perceive the paternalistic features of a technology. Factors such as perceived restrictions on freedom or job security should be considered when designing smart products. In addition, paternalistic aspects can be mitigated, for example, by providing more customization options. Including options to interrupt autonomous processes or configuration options to determine the most appropriate level of assistance can increase user acceptance.

The results of this study raise the question of to what extent users want to be informed by a smart product about its actions and decisions. This may be relevant for practitioners designing smart products that are intended to be completely ubiquitous without communicating with the user at all.

TP should be interpreted on an individual basis, as the perception of autonomy is highly dependent on individual characteristics, such as the user's experience of using smart products (Logg et al., 2019). When designing a smart product for a particular user group (e.g., experienced workers), taking into account individual characteristics, such as task experience and smart product experience, may be important.

Finally, this study provides food for thought for managers regarding the use and implementation of smart products for employees (e.g., in warehousing). Managers can gain insight into the relevant factors that influence employees' perceptions of TP. This must be considered when implementing smart product use among employees with different levels of task and technology experience. The use of smart products in a professional environment should be treated with caution, as there is potential for consumer backfire related to TP.

2.4.3 Limitations and future research

As with any research endeavor, there are limitations to this work. Although the search terms, inclusion criteria, and forward and backward searches provide a rich foundation for a literature review, it is likely that there are scientific papers that were not included in this work. Future studies could provide a more complete inventory by including studies published in other languages. In addition, the author cannot rule out the possibility of publication bias. There may be unpublished manuscripts that would enrich the literature used in this review.

Future research on this topic should address a variety of aspects of TP, such as how the effects of TP on user acceptance of technology can be mitigated or eliminated. To answer these and other questions, it is necessary to quantify the construct of TP. Therefore, the development of a measurement scale should be one of the next steps. It is also necessary to explore how to optimize the balance between providing valuable information to the user and potential information overload. In addition, it may be important for product designers to understand which features of smart products are perceived as particularly paternalistic. This may help product design and development avoid implementing highly paternalistic product features.

Smart products include not only products able to autonomously perform a specific task, but also those capable of learning, anticipating, and acting independently of user intervention (Raff et al., 2020). However, to be considered paternalistic, a product must act autonomously. A product that acts only with the user's consent cannot develop paternalistic characteristics at all, since the user always "has the last word". This leads to the assumption that the autonomy condition presented in this paper could be a precursor of TP.

Third, users' expectations of smart products may differ significantly according to individual characteristics, such as age, gender, ethnicity, education level, and personality (Q. Zhang et al., 2022). In contrast, Wanner et al. (2022) reported non-significant moderating effects of age, gender, and experience on performance expectancy and effort expectancy in the context of smart product acceptance. Given this area of tension and the fact that the degree of reactance arousal is an individual matter (Steindl et al., 2015), investigating how these characteristics actually moderate the perception of TP will be a valuable topic for future research. Hence, it may also be valuable to examine the mediating effects of individual characteristics.[4]

Finally, it may be helpful to consider TP from an interdisciplinary perspective. Certainly, TP can be positive, for example, when a product seeks to protect the user. However, restricting individual freedom in the context of TP is at least ethically questionable. From a legal point of view, it is also questionable whether the manufacturer of a product is allowed to reduce consumer protection to reduce the paternalistic effects of the technology.

2.4.4 General discussion

The growing importance of smart products, increasing computing power, the steady growth of the Internet of Things, and the resulting increase in the number of connections between smart products will lead to a huge increase in the importance of TP in coming years. Artificial intelligence is already superior to humans in several areas, such as gaming (AI won against the human master of the game of Go without prior examples or human instructions (Hutson, 2017) or creating floor plans on microchips (Kahng, 2021). Furthermore, the quality of anthropomorphic design is steadily increasing, meaning that smart products are increasingly perceived as social agents, leading to perceived human–human-like interactions instead of clearly identifiable human–computer interactions (Hermann, 2022). This rapid evolution of AI leads to further questions related to TP. For example, do we need policy initiatives to prevent TP from getting out of hand? The rapid evolution

[4] I would like to thank a reviewer for this valuable suggestion.

of AI and traditional legislative inertia will mean smart product developers and consumers need to answer the question, "How much control do we give to technology? "

CHAPTER

3

PAPER II

Technology paternalism: Development and validation of a measurement scale

3. Paper II: Technology paternalism: Development and validation of a measurement scale[5]

Abstract

As technologies become smarter, they tend to protect their users, much like parents protect their children. However, caring too much about a user can lead to technology paternalism, a construct that is becoming increasingly relevant with the advent of smart technologies. Nonetheless, very little is known about what technology paternalism is or how it can be measured. The authors applied established procedures from scale development methodology followed by quantitative measurement to present and validate a three-factor scale (limiting, overruling, and welfare). The approach offers first empirical evidence linking technology paternalism to associated concepts, showing that it correlates as expected with established constructs in the literature on technology acceptance. This study contributes to the literature by uncovering a construct of interest to a critical discussion of technology paternalism and by providing a measurement tool that can be used by researchers, policy makers, and managers.

Keywords: paternalism, scale development, smart technologies, technology acceptance, technology paternalism, technology resistance

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The formatting and content of this chapter (e.g., headings, citation style, table numbers) may differ from the published version. A CRediT author statement for this publication can be found in the appendix (Table 38).

3.1 Introduction

Smart products are becoming increasingly common due to digitization. These products gather, process, and produce information, and have capabilities that "traditional" products (e.g., regular watches) do not have. For instance, they can act without needing explicit input from the user, adapt to new situations, and interact with the user, other devices, or other stakeholders around them (Raff et al., 2020). While beneficial, functional features alone can't explain consumer behaviors, attitudes, and technology adoption (Chitturi et al., 2008). Although these features enhance efficiency, they may also lead to resistance or reduced acceptance due to perceived loss of control (Rochi, 2023). Examples are the NEST Learning Thermostat[6] or autonomous cabs offered by Cruise.[7] Past research indicates consumer preference for smart technologies due to their superior capabilities (e.g., Porter & Heppelmann, 2014 and Davis, 1989). However, scholars have also shown that these new capabilities can also lead to consumer resistance, for instance, by reducing user well-being (Su et al., 2014), trust (Vimalkumar et al., 2021), comfort and security (Chang & Chen, 2021), or perceived enjoyment (J. Lee et al., 2019).

In this research, we apply the concept of paternalism to technologies and human–computer interaction: technology paternalism (TP). An everyday example is loudly beeping cars that annoy us if we drive without fastening our seatbelt. This sound may be perceived as a freedom-cutting annoyance, and drivers cannot overrule it without expert knowledge. It is claimed to be in the interest of the driver, as it increases driver safety or welfare (Spiekermann & Pallas, 2006). Thus, TP can be understood as a freedom-cutting action of technology that is promoted as being in users' interests and cannot be easily overridden. We will leave this as the first working definition, referring to a more detailed definition in the corresponding section.

TP is a largely overlooked area in acceptance and resistance research, lacking empirical evidence and primarily existing as anecdotal or conceptual insights. Notably, only a few scholars (Hilty, 2015; Kinder et al., 2008; Rochi, 2023; Spiekermann & Pallas, 2006) have delved into TP in significant detail. Comprehending TP is vital for understanding how consumers perceive technologies designed to protect or care for their users. Smart products, akin to parental behavior, might be seen as "overprotective" or "controlling. " Despite its potential

[6] The Nest Learning Thermostat is a smart thermostat, which learns your schedule, programs itself, turns down the heat when you're away.
[7] Cruise autonomous taxis, a subsidiary of General Motors, provides self-driving vehicles without the need for a human driver.

importance, TP has only been measured by Schein and Rauschnabel (2022), who used a four-item ad hoc unidimensional scale.

Technology operates based on the rules programmed into it, which raises the question of whether TP depends on those who set the operating rules (algorithms) for these products. In this context, development engineers, companies, or governmental entities may be the first agents of TP that come to mind (Millar, 2015). Nevertheless, this paper does not focus on the question of "Who are the real patrons? " (Spiekermann & Pallas, 2006, p. 12). Rather, it contributes to the body of knowledge by addressing the empirical gap in users' perceptions of TP. We developed a theoretically sound measurement scale for assessing perceived TP in smart products, utilizing both qualitative and quantitative studies. Our approach, guided by established scale development procedures, offers preliminary empirical evidence linking TP to antecedents, associated concepts, and consequences. The next section introduces smart products and TP in detail, and then places TP in the canon of related concepts and theories. Section 3 introduces the research methodology and all five studies in detail. Finally, a general discussion addresses theoretical issues, practical implications, limitations, and avenues for future research.

3.2 Theoretical background

3.2.1 Smart products

Academics use several terms to describe smart products, such as intelligent products (Raff et al., 2020), smart objects (López et al., 2011), and smart technologies (Roy et al., 2018). In our study, we treat terms like intelligent products and smart things equally, defining a smart product as a device capable of learning, anticipating, and acting independently (Raff et al., 2020). We also consider it to have both a physical and a digital part (Pardo et al., 2020). A smart product has to "address usage on its own" (the physical part) (Pardo et al., 2020, p. 207) and connect itself with a larger network (Raff et al., 2020) to interact with other smart products or humans (Monostori et al., 2016). They exhibit proactive behavior through predictive analytics (Raff et al., 2020) and share, augment, and comprehend the contextual information they gather (Kumar et al., 2024; Mitew, 2014). A smart product "does not need human intervention but instead takes over on its own" (Rijsdijk & Hultink, 2003, p. 206) as it is able to learn, act, and independently set goals (de Bellis & Johar, 2020;

Rijsdijk et al., 2007) to deliver value to the user. Hence, through their capabilities, smart devices may interact with people as social entities (van Doorn et al., 2017).

3.2.2 Technology paternalism

Defining Technology Paternalism

Paternalism is a well-known phenomenon in interpersonal or individual–government interactions. In this context, it is defined as "the interference of a state or an individual with another person, against their will, motivated by a claim that the person interfered with will be better off or protected from harm" (Dworkin, 2020, para. 1). From the perspective of a paternalized person, paternalism can be perceived as personally damaging behavior (Farh & Cheng, 2000) and may lead to counterproductive action (Daniels & Jordan, 2019). In a family context, parents often make paternalistic decisions for their children, including choices about food or TV consumption. Despite well-meaning intentions, differing preferences may lead the child to feel paternalized. Paternalism can also occur between economically acting organizations and employees (e.g., in labor control or industrial safety; Kinder et al., 2008) or between large companies and smaller suppliers (e.g., dictating quality control procedures; Aycan, 2006). Paternalism can also appear in interactions with smart products, since "if objects sense what is rightful and what isn't and based on this information limit or castigate peoples' actions, they effectively become paternalistic" (Spiekermann & Pallas, 2006, p. 9).

Wirtz et al. (2018) suggested that users' acceptance of smart technologies can be influenced by social-emotional elements, like the psychological evaluation of the product as a social presence in their lives. Drawing on the work of Spiekermann and Pallas (2006), we define TP as the autonomous action of a technology claimed to be in the user's interest, directly affecting them, perceived as limiting freedom, and not overrulable without sacrificing functionality. Note that other definitions include autonomy as a dimension of TP (e.g., Spiekermann & Pallas, 2006), but we consider "product autonomy" as a prerequisite of TP (Rochi, 2023), since intelligent technologies by definition act autonomously or independently (Raff et al., 2020). In the absence of autonomy, technology can act only on behalf of the user or perform user-initiated actions, which precludes TP.

Potentially paternalistic technologies surround us, understand our context, and can judge what is right or wrong (according to algorithms). Examples can be taken from the interviews conducted in our qualitative

Study II.1 (introduced in detail in section 3.3.1). For instance, interviewee P5 stated that he felt disregarded by autonomously undertaken back-ups "because the decision was just made on its own, without [me] being included, without me wanting a security backup to be made. " In this case, the technology initiated a backup without user consent, impacting perceived user competency and freedom. While this service can be disabled, it involves a tradeoff (data security). The action aims to benefit the user by ensuring regular data saving, covering the three stated TP dimensions: limiting user freedom, overruling the technology, and the welfare intention behind technology actions. In this section, we draw on existing research to conceptually support each dimension of TP.

Limiting user freedom

Smart products may diminish our autonomy competencies, making us more vulnerable (Formosa, 2021). According to Rochi (2023), TP may cause users to perceive a loss of freedom or a threat to a certain behavior, which leads to an attempt to restore behavioral freedom (e.g., developing product resistance). This phenomenon is also known as reactance (Miron & Brehm, 2006). For example, if an autonomous car slows down against the user's will, they may feel that their autonomy is threatened. If users can reverse the decision and regain freedom, they may do so. In cases where regaining freedom is not possible (e.g., due to required programming knowledge or default settings), this may result in a changed product evaluation, leading to a lower adoption intention or stronger resistance (Rochi, 2023).

Overruling the technology

Smart products have the potential to deliver better performance, customization, and customer value compared to conventional alternative products (Porter & Heppelmann, 2014). Consumers may lose value and functionality when they override the actions of smart products. However, intervention design is crucial for fostering the adoption and use of information technology (Venkatesh, 2022). If the functionality of a smart product cannot be easily changed or turned off (because it requires expert knowledge, e.g., programming skills), this may place the consumer in a paternalistic relationship with the device (Millar, 2015; Sørensen & Schmidt, 2016).

Welfare intentions behind technology actions

Smart products aim to promote user welfare, such as autonomous shopping assistants and recommendation agents that aim to reduce search time and costs. These algorithms aim to ensure users receive a manageable amount of relevant and interesting information. However, they may potentially undermine individual decision-making, deprive users of crucial information, limit the opportunity to expand horizons, and reduce perceived personal freedom of choice, subsequently decreasing usage (Appelgren, 2019; Helbing et al., 2019). The welfare intention dimension is particularly important for the perception of TP. Without welfare intention, an action by a smart product cannot be perceived as paternalistic, and potential threats to freedom or a lack of overruling options may be perceived as simple autonomy cuts. Hence, a key aspect of paternalism is the intention of user welfare in the overruling or freedom-threatening action.

Antecedents and Consequences of TP

The perception of TP emerges from consumer–smart-technology interaction (Rochi, 2023). As this perception is dependent on user and technology characteristics, we propose technology autonomy as an antecedent of TP. Further, we predict that lower usage intention is a consequence of higher levels of perceived TP. We empirically test these assumptions in Section 3.3.6.

Antecedent: Technology autonomy

To enhance user experience and adapt to usage scenarios, smart products gather and analyze substantial volumes of personal data and context (Karwatzki et al., 2017). This data collection often takes place covertly or without user consent, causing a sense of compromised autonomy (Yost et al., 2019). In most cases, it is not easy to overrule smart products' autonomous actions (without expert knowledge), which results in a perception of TP (Rochi, 2023). Recent research by Lucia-Palacios and Pérez-López (2021) shows that increasing product autonomy leads to a loss of control, thereby increasing the perception of intrusiveness, which is likely to lead to TP. Thus, we expected a positive correlation between technology autonomy and TP.

Consequence: Usage intention

Limiting customer control may impact the market success of smart products (Zimmermann et al., 2023). High product autonomy can lead to a perception of reduced user control (N. Schweitzer et al., 2019). Moreover, current limitations of smart technologies in adapting to unusual queries and fully understanding complex user context (Ameen et al., 2021) leave users to decide how to modify processes and respond to changing conditions (Meissner et al., 2020; Schein & Rauschnabel, 2021). However, when users lack adaptation or overruling options, they resort to evasive tactics to bypass the system or avoid undesirable actions (Kinder et al., 2008), which reduces usage intention (Rochi, 2023). According to the technology acceptance model (TAM) and the unified theory of acceptance and use of technology, perceived usefulness, effort expectancy, and performance expectancy are the main indicators of intention to use a technology (Davis, 1989; Venkatesh et al., 2012). Considering TP as a factor negatively affecting behavioral intention through these constructs (Rochi, 2023), we predicted a negative correlation with perceived usefulness, effort expectance, and performance expectance.

Differences and Interrelationships with Related Concepts

To comprehend the significance of TP, it is essential to examine its differences and connections with related concepts (e.g., technology intrusiveness) and theories (e.g., psychological reactance theory or technology acceptance theories). In doing so, the importance of considering TP in marketing and other disciplines is highlighted, as it offers a new perspective on technology adoption research. For instance, according to TAM, external factors (e.g., design features) lead to cognitive responses, including perceived ease of use and PU (Davis, 1989, 1993), which consequently influence users' adoption intentions. Therefore, TP can be seen as such an external factor (e.g., as a combination of design features) influencing those cognitive responses. In contrast, TAM postulates that increasing usefulness and ease of use always leads to a more positive attitude toward a technology. However, this "the more value/service the better" hypothesis might not automatically hold true with all smart products. At a certain point, excessive advice, support, or information can result in lower adoption (Rochi, 2023) (for a detailed discussion of interrelationships and differences between TP and related concepts and theories, see Table 4). Based on the above considerations, we developed an initial conceptual model (see Figure 5).

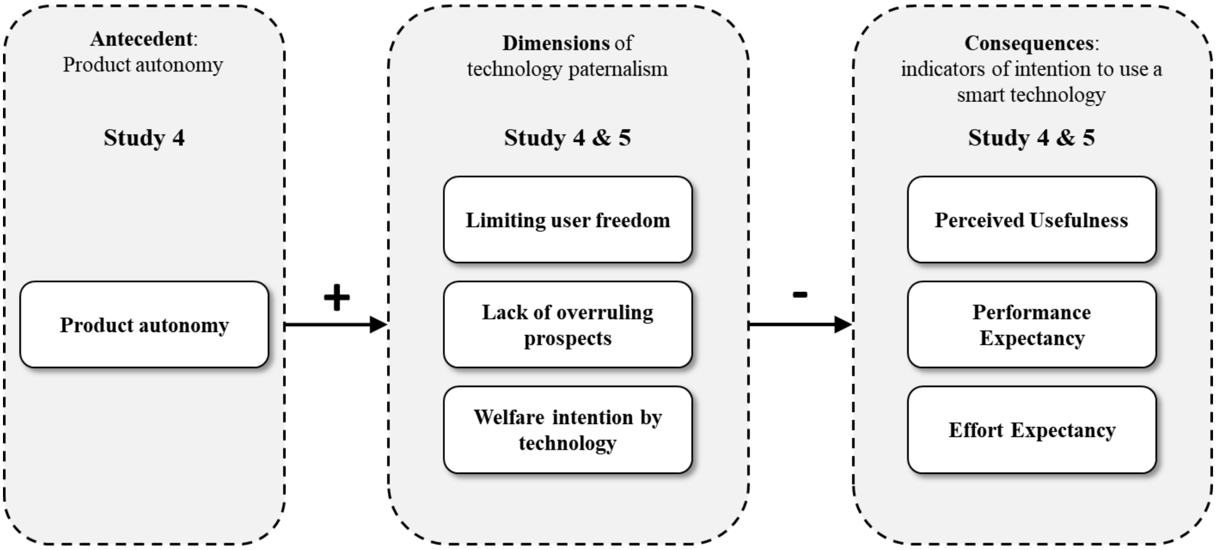


Figure 5: Conceptual model of technology paternalism, proposed antecedents, and consequences

Table 4: Interrelations and differences with other theories and related concepts

Theories				Nearby concepts	
The Technology Acceptance Model (TAM) (Davis, 1989)	**The Theory of Planned Behavior (TBP) (Ajzen, 1991)**	**The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003)**	**Psychological Reactance Theory (PRT) (J. W. Brehm, 1966)**	**Technology Intrusiveness (TI)**	**Algorithm aversion (AA) (Jussupow et al., 2020)**
Main assumptions Prediction of the acceptance of IT in work environments. Focus on individual-level adoption. Acceptance of technology is a three-step process where external factors initiate cognitive responses, like perceived ease of use (PEOU) and perceived usefulness (PU) (Davis, 1989, 1993), which are significant factors in determining an individual's acceptance of a technology. The stronger the behavioral intention (BI) to use the technology, the more likely the individual is to use it.	**Main assumptions** Explains and predicts human behavior in relation to goal-directed actions. Individual intention to engage in a specific behavior is a reliable predictor for actual behavior. A positive attitude toward the behavior increases the likelihood of forming an intention to perform it. Perceived behavioral control influences both behavioral intentions and actual behavior.	**Main assumptions** Assumes that individuals are more likely to adopt a technology if they believe it will positively impact their performance. Behavioral intention and subsequent behavior are directly influenced by four key factors: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). These factors are moderated by gender, age, experience, and voluntariness of use.	**Main assumptions** People have a need for freedom and autonomy, valuing their ability to make choices and control their actions (J. W. Brehm, 1966). Provides insights into how individuals respond to perceived threats to their freedom and autonomy (Youn & Kim, 2019). Reactance (R) is a motivational state, driving freedom restoration (Rosenberg & Siegel, 2018). People experience reactance, when something threatens or eliminates freedom (Rosenberg & Siegel, 2018).	**Main assumptions** Focus on collection, usage, and storage of individual data to observe and control user behavior (Lucia-Palacios & Pérez-López, 2021). TI negatively impacts technology adoption (Boeck et al., 2011; Hérault & Belvaux, 2014) and leads to less acceptance of messages provided by the technology (van den Broeck et al., 2019) Smart products can be perceived as intrusive because they can act without user permission (Mani & Chouk, 2017).	**Main assumptions** AA is defined as biased assessment of an algorithm, which manifests in negative behaviors and attitudes towards the algorithm compared to a human agent (Jussupow et al., 2020). AA is the reluctance of human predictors to use superior but imperfect algorithms (Burton et al., 2020).
Definitions of key aspects (Davis, 1989): PU: refers to an individual's perception of the extent to which using a particular technology will enhance their job performance or make their tasks easier to accomplish. PEOU: an individual's perception of the effort required to use a technology. BI: a strong predictor of actual system use. It is influenced by PU and PEOU. External factors: external factors, such as social influence, organizational policies, and support, can influence an individual's PEOU, PU, and intention to use a technology.	**Definitions of key aspects (Ajzen, 1991):** Behavioral intention (BI): an individual's willingness to perform a specific behavior. It is influenced by the individual's attitudes (A), subjective norms (SN), and perceived behavioral control (PBC). A: an individual's overall evaluation of the behavior. SN: the perceived social pressure or influence surrounding the behavior. Playing a vital role in shaping behavioral intentions. BC: an individual's perception of the ease or difficulty of performing the behavior.	**Definitions of key aspects (Venkatesh et al., 2003):** PE: user perception that using a technology will improve job performance. EE: User perception of the ease of use and effort required to adopt/use a technology. SI: influence of social factors on individual technology adoption decisions. FC: The presence of necessary resources, support, and infrastructure to facilitate technology adoption and usage. BI: User intention to use a technology.	**Definitions of key aspects (J. W. Brehm, 1966; Dillard & Shen, 2005; Miron & Brehm, 2006):** PR: the motivational state that is hypothesized to occur when freedom is eliminated or threatened Reactance occurs when individuals perceive a threat to their freedom, motivating them to restore their autonomy. Threats to Freedom: Various forms of restrictions or limitations can trigger reactance. Individuals actively seek to regain their freedom and autonomy when it is threatened, often through behaviors that defy restrictions.	**Definitions of key aspects** On product level, TI refers to the ability of a technology to enter the consumer's life without permission (Mani & Chouk, 2017). On company level, intrusiveness is defined as "the consumer's perception that the company abusively penetrates into his/her private life" (Boeck et al., 2011, p. 843). The information processing capabilities of smart products, like collecting, storing, using information, demonstrates competence but also shows its intrusive nature (Aw et al., 2023).	**Definitions of key aspects (Jussupow et al., 2020):** Algorithm agency: whether the algorithm performs tasks autonomously. Algorithm performance: algorithm failures and its reliability rate. Perceived algorithm capabilities: whether the algorithm is perceived to have the needed capabilities to perform the task. Human involvement: how strongly humans are involved in training and using the algorithm.

Table 4 continued: Interrelations and differences with other theories and related concepts

Interrelations: According to TAM, external factors (such as design features) initiate cognitive responses, including PEOU and PU (Davis, 1989, 1993). Hence, TP, with all its sub-dimensions, may be perceived as an external variable. In the first place, welfare intention and product autonomy may impact PEOU or PU, both positively and directly, because both factors can increase product value. But, when too much support intention of the product leads to TP, the autonomy and welfare intention of the product may influence technology acceptance negatively. Furthermore, limiting user autonomy and offering restricted override options can lead to effects like loss of control and can increase perceived TP, which consequently leads to lower product acceptance (Rochi, 2023).	**Interrelations:** A perceived autonomy cut, or a lack of overruling prospects may affect BC, which reduces the intention to adopt a technology. The welfare intention is two-edged. In the beginning, the increased value of the product (due to higher autonomy or services offered) may affect the attitudes of the user positively, as this product may make life easier. Nevertheless, from a certain point on, too much advice, information given, etc., will lead to a negative effect of the welfare dimension of TP on BC. Furthermore an (un)favorable evaluation of the behavior of adopting a smart product depends on individual characteristics, (e.g., need for cognition) which may be affected by the autonomy cut or the lack of overruling prospects (Rochi, 2023). Social norms may have links to the perception of TP as well. In certain cultural environments, cultural dimensions like individualism/collectivism or indulgence/restraint (Hofstede, 2011) influence social norms and consequently may influence the degree of perceived TP (e.g., the indulgence/restraint dimension).	**Interrelations:** The interrelations of TP and UTAUT are somehow analog to the links of TP and TAM. TP may be interrelated with PE and EE. The perception that using a technology improving the own job performance and the perception of the ease of use to adopt a technology may decline when a technology is perceived as paternalistic (Rochi, 2023). When a paternalistic technology cuts user autonomy and offers not enough overruling prospects, this reduces PE and EE. SI show similar links to TP as social norms from TPB. SI may be subject to effects by TP as well. Social norms, opinions and recommendations to use technology are subject to cultural differences. (S.-G. Lee et al., 2013). FC may be affected positively in the first place, as autonomous smart product characteristics can ease the usage of a technology. Nevertheless, from a certain point on, too much information, advice or service may lead to a stronger perception of TP, leading to lower FC and therefore lower BI to use the product.	**Interrelations:** PRT has strong links to all three dimensions of TP (Rochi, 2023). Autonomy cut: by restricting the user's freedom, smart products threaten the individual's free behavior, leading to the arousal of reactance (Youn & Kim, 2019). Lack of overruling: By limiting the ability to override, smart products threat the free behavior of individuals, which leads to the arousal of reactance. For instance, option limitation may lead to reactance arousal (Schlosser & White, 2007). Welfare intention: Honorable reasons for autonomous actions of smart products can lead to perceived paternalism, which threatens the free behavior of individuals and leads to the arousal of reactance. For instance, reactance can occur towards recommendations (Aljukhadar et al., 2017; Fitzsimons & Lehmann, 2004) or ad personalization (Bleier & Eisenbeiss, 2015).	**Interrelations:** Certain smart products´ specific features (like regular notifications to remind on something or tracking the usage context) can interrupt consumers (Mani & Chouk, 2017). Users become conscious of the technology's intrusiveness when they receive unsolicited information about products or services. They become aware that the smart device has activated without their explicit instruction and has discreetly recorded and collected information from the user and people nearby, which is then disclosed to service providers (Lucia-Palacios & Pérez-López, 2021). This can be perceived by consumers as threatening their freedom (Aw et al., 2023; Ogbanufe & Gerhart, 2022). This perceived cut of autonomy is a strong link to the concept of TP, showing the relation between both, TP and TI.	**Interrelations:** The key aspect of AA is algorithm agency, which is strongly shaped by how the user examines the algorithm's proposals (Komiak & Benbasat, 2006). One reason for different interactions with advisory compared to performative algorithms is a perceived loss of control (Burton et al., 2020). This shows a strong link to the perceived autonomy cut dimension of TP. A loss of control drives both concepts, TP and AA. Algorithm performance perceived algorithm capabilities show connections to TP as well. Perceived algorithm capabilities are a driver for AA as algorithms are often perceived to lack competences which are necessary for a task (Jussupow et al., 2020) or to be unable to account for the users' unique characteristics (Longoni et al., 2019). This can be connected to the lack of overrule prospects dimension of TP. If a technology/an algorithm lacks adaptation capabilities (e.g., overruling certain functions), this increases both, TP and AA.

Table 4 continued: Interrelations and differences with other theories and related concepts

Main differences: TAM was introduced to investigate the acceptance and use of IT in work environments. But first of all, TP is a matter of personal perception, which is highly influenced by the fact if the technology is used by order or by free will. If a technology must be used by management order (e.g., in a warehouse) the perception of TP may be much lower than in a context with free usage choice. If you must use the technology anyways, why bothering when it acts like a father or a mother to you as the user? Second, TAM proposes that increasing PU and PEOU result in higher attitude towards using and higher BI. But this “the more support the better” assumption does not necessarily hold true with smart products. From a certain point on, too much advice, support, information, etc. can be perceived as paternalistic, resulting in lower adoption.	**Main differences:** One of the criticisms of TPB is of its focus on rational reasoning and its lack of subconscious, associative and impulse factors, feelings, and private standards (Sniehotta et al., 2014). Hence, as TP strongly affects personal feelings and private or personal standards, is a neglected factor in the TPB framework.	**Main differences:** UTAUT lacks variability within the context of adoption and use (Dwivedi et al., 2019). UTAUT overlooks the role of the individual characteristics (Oh & Yoon, 2014). Previous studies have emphasized the importance of individual characteristics such as computer self-efficacy and personal innovativeness (e.g., Chong (2013; Venkatesh et al.). Furthermore, attributes unique to specific technologies (like smart products have) play a vital role in the adoption of those technologies (Brown et al., 2010; Hong et al., 2014). Hence, UTAUT neglects the fact that modern smart technologies hold new capabilities, which may let them become paternalistic.	**Main differences:** Besides its strong links to TP, PRT needs to be more interpreted as a potential consequence of TP. The perception of TP leads to the arousal of reactance (Rochi, 2023). And the consequent arousal of reactance leads to less positive evaluations of paternalistic products (M. A. J. Roubroeks et al., 2010).	**Main differences:** Because of the high congruence between both concepts, one can imagine that paternalistic technologies may be perceived as intrusive. But not all intrusive technologies are necessarily paternalistic. One main reason for this is the welfare dimension of TP. The intention to make the user better off is a necessity for TP to develop. Without this intention, the technology cannot be perceived as paternalistic.	**Main differences:** TP and AA show a strong link when it comes to the effect of perceived loss of control. But for TP, a loss of control alone does not lead to the arousal of perceived paternalism by a technology. The welfare intention and a lack of overruling prospects is necessary to percept TP. AA is, compared to TP, a more general concept which investigates the overall attitude towards an algorithm (which does not necessarily need to have the abilities of a smart technology).

3.3 Research Methodology and data analysis

We conducted an initial qualitative construct specification of TP by analyzing the content of 15 qualitative interviews (Study II.1). Based on the results, we generated a set of potential items in Study II.2. Study II.3 aimed to reduce the list of potential items through expert and consumer validation. In Study II.4, we used exploratory factor analysis (EFA) to determine the number of dimensions to retain. Study II.5 included a validation study based on a confirmatory factor analysis (CFA) to corroborate the factor solution from Study II.4. We provide preliminary evidence on nomological validity with additional data from Studies II.4 and II.5 in Section 3.6.

3.3.1 Study II.1: Qualitative construct specification

In Study II.1, semi-structured in-depth interviews were conducted to identify the dimensions of perceived TP [N = 15; 67% male, aged 22–59 years, M= 31 (SD = 13) years]. All participants had experience using smart devices. The interviews began with some general questions about smart technology use and ensured a common understanding of smart technologies. To obtain diverse perspectives, we utilized a sample of participants with different genders, professions, technology use, and sociodemographic backgrounds. To define the number of interviews, we applied the concept of theoretical saturation, meaning that data collection continued until further interviews did not generate additional insights (Matthes et al., 2017). After 10–11 interviews, we found that no new information was being drawn from additional interviews (Glaser & Strauss, 2017).

Since the interviews generated text in a free-form manner based on the informants' input, we utilized interpretative techniques for data analysis for construct specification. We included suggestions from thematic analysis for theory building and conducted a coding process using open, axial, and selective coding (Boyatzis, 1998; Corbin & Strauss, 2015; Felix et al., 2017). During the initial phase, open coding was employed to meticulously analyze the data on a line-by-line basis. Through this process, we systematically generated preliminary categories using probing and comparison techniques (Goulding, 2005). In the subsequent stage, axial coding was deployed to reveal overarching second-order themes, elevating the analysis to a more abstract level. This stage involved linking concepts that emerged during the open coding stage through a "compare and contrast" approach (Felix et al., 2017, p. 120). The final step, selective coding, involved merging and solidifying axial codes into higher-level second-order categories. Our analytical framework followed the inductive procedure elucidated by Homburg et al. (2017).

Interview results

The interviews revealed three second-order dimensions of perceived TP. These dimensions showed strong equivalence with the preliminary definition of TP described above. Restriction of freedom was a major theme that emerged repeatedly. Giving up autonomy to become safer seemed desirable to some study participants, but many indicated that giving up control and letting smart technology decide was not an option. They also stated that they wanted to be informed about the basis for the technology's actions to understand its decisions. Ways to override the technologies and regain control were also mentioned regularly. Respondents expressed that it was important that the autonomous technology actions made sense to them; otherwise, they would prefer to have control. One respondent emphasized that human decision-making should always come before technological decision-making and that humans should always be able to interrupt technological decision-making processes.

In contrast, other respondents indicated that they had great confidence in the decision-making authority of technology. The feeling of being protected versus the loss of autonomy received mixed opinions in the interviews. Therefore, the situation in which a technology makes decisions plays a key role in whether it increases or decreases TP. Table 5 summarizes the exemplary statements, interpretations, and dimensions that emerged from the qualitative interviews. Additionally, respondents provided few to no statements on product autonomy playing a key role when perceiving TP. One reason for this could be that all technologies assessed in the interviews were judged autonomous from the outset. This supports our assumption that product autonomy is a prerequisite for TP (see Section 3.2.2).

Table 5: Exemplary statements, interpretations, and dimensions of qualitative interview results

Statement examples	Interpretation
Limiting user freedom	
“I think I am still old enough and I have my own senses to decide what I want to drink, what I want to do, and when I want to drink my coffee and how.” Interviewee P2 “If I say I want to get out here now and the car won't let me, then the car is taking me as a prisoner. That is holding a person captive. And that is not okay. No matter what the reasons are.” Interviewee P1	Sacrificing decision power to a technology leads to cutting of freedom, resulting in an increase of perceived TP.
“It would bother me more if the car decides to slow down because of drizzle. However, it would also be safer. Accordingly, again, it would be an internal process. How much [speed] is reduced? How much is it costing me in time now? Does it have to be done now? How much is it raining? Quite a lot of factors.” Interviewee P4 “Because the decision was just made on its own, without [me] being included, without me wanting a security backup to be made, suddenly, my cloud was full.” Interviewee P5 “And that would be nice if the technology immediately said, ‘I'll reduce the speed to 130.’ That’s a difference of two kilometers [compared to the lead when speeding]. Thus, a difference [in terms of a time loss] of 42 seconds.” Interviewee P4	The interviewee wants to be notified about the information that forms the basis for the technology’s action, to understand its decision. This is interpreted as the participant perceiving a loss of competence through a lack of understanding of the actions made by the technology, which increases perceived TP. Interviewees expressed concern about the lack of transparency of the decision-making process of the technology and when it acts. Furthermore, the desired density of information when interacting (with a smart autopilot) plays a vital role. This is interpreted as the participant perceiving a loss of competence through a lack of understanding of the actions made by the technology, which increased perceived cuts to freedom.
Lack of overruling prospects	
“However, if the reasons seem incomprehensible to me, I probably want to reject it at that moment.” Interviewee P7 “This is probably because in most situations, assuming it is really about something more serious, like life and death, the human being then simply also really considers the seriousness of the situation completely, and also works with feelings, and not simply purely logically like a machine, and therefore I would simply trust the human being more, that he really wants the best for me.” Interviewee P13 “I simply believe that the human being is an instance that should never be missing, because sometimes there are decisions to be made that a computer can never make. […] I didn’t really feel safe [when trying autonomous features in a car]. Even with this brake, this automatic brake that’s sold in a lot of cars now. I know it very likely works, but I don’t trust it completely, and I don’t really feel safe with it.” Interviewee P13	The interviewees stated that they wanted to be able to overrule the technology in the case of perceiving a cut to their freedom (e.g., through a lack of understanding what the technology is actually doing) or any other liming action by the technology. If actions cannot be interrupted by the user, they may feel overruled by the technology or even feel captive and powerless. This is interpreted as the participant perceiving a lack of personal freedom to move whenever they want. Furthermore, interviewees stressed the role of the person as the final decision maker. Here, the issue of trust in the technology plays a vital role. Participants stated that they believed that humans make better-informed decisions than smart technologies, and they did not trust the technology or just believe that humans have more decision-making competence than smart technologies. Therefore, overruling options for the user must be offered in any situation so they can regain control if necessary. If this is not the case, users perceive a lack of causal agency, which results in TP.
“I think that our technology is already very advanced these days and [the technology] can measure the extent to which this [interrupting or correcting an action made by a human] is necessary or not. That’s why I would actually trust the machine when it says, ‘Hey, something’s wrong.’” Interviewee P3 “I trust the machine, well, I trust the technology to know better than I do right now.” Interviewee P3 “If the machine gets more input, i.e., gets more of the external circumstances of the situation, it probably makes more sense to listen to the machine than to the human, but if the human has more experience in the situation anyway, and he also has more of an overview of the situation, I will listen to the human.” Interviewee P13	Some interviewees stated that they highly trust in the decision-making competence of the technology. In this case, the need for overruling opportunities is lower, and so is TP.
Welfare intention of technology	
“It’s dangerous if AI becomes so sophisticated that you can’t make any more decisions. I’m ambivalent about it, but in this car example [autonomous actions made by autopilot], I don’t think it’s [losing decision making power] so bad, because I believe that it will simply serve safety at some point.” Interviewee P4 “I believe that the more severe the consequence of a wrong decision, the greater the acceptance of this restriction [in autonomy].” Interviewee P5 “I think freedom is a very important good, and it should be restricted only for important reasons, such as directly saving lives or preventing traffic accidents.” Interviewee P7	The importance of the situation in which a technology makes decisions plays a certain role. The more aware the user is of the welfare function of the technology, the less TP they will perceive.

3.3.2 Study II.2: Item generation

After obtaining information from consumers about their perceptions of TP, we developed an item pool by identifying specific interview statements (i.e., potential items). Our analysis of interview transcripts, conducted by two coders, resulted in the identification of 163 statements, several of which were deemed redundant and removed through discussion, leaving 74 statements. In addition to these statements, we incorporated items from prior journal and conference publications (e.g., Paetzold, 2021; Schein & Rauschnabel, 2021), even though they lacked an established systematic scale development process, to ensure that all possible nuances were covered. The combination of these statements and items resulted in 89 potential items.

3.3.3 Study II.3: Item revision

To limit the number of potential items for quantitative methods and for content and face validity, we collaborated with experts and consumers to validate all 89 generated items for their fit. Informants were recruited from academia and practice via professional and private social networks and cold calling (see Table 33 for an overview of all participants). Before sending the items for validation, we discussed the context and validation process with each expert separately.

First, we introduced the purpose of the paper. Then, we distributed all statements in random order in a spreadsheet. We asked our informants to rate all 89 items on two criteria: face validity ("To what extent do you think this statement is related to paternalism through technology?") and clarity of expression ("How clear do you think is the wording of this statement?"). Respondents then rated each item on a 7-point Likert scale. For each item, informants could add a comment (e.g., recommendations for improvement). We also asked about missing statements (none were mentioned in the evaluation process). The informants had several days to complete this task, and three experts verbally added their insights and ideas after the process. We excluded low-scoring statements to reduce the item lists. For the final selection of potential items, we considered only those rated as 4 or higher by at least 75% of respondents regarding face validity and clarity of expression. To assess the robustness of the cutoff criteria, we performed replications with different thresholds, which led to comparable results with only minor differences. In the end, we combined both item lists (face validity and clarity of expression) and excluded duplicates, resulting in a final set of 28 items (see Table 6).

Table 6: Final pool of items for EFA (Study II.4)

No.	Item
1	The technology makes decisions without involving me.
2	I can't ignore the rules of technology.
3	The technology makes me lose freedom of choice.
4	The technology is authoritarian.
5	The technology interferes with my affairs.
6	The technology wants the best for me, even if that means overruling me.
7	The technology ensures that I follow rules.
8	The technology ensures that I follow regulations, even if I didn't intend to.
9	The technology overrides my desires.
10	I feel like I'm externally controlled by the technology.
11	I have to accept the decision of the technology.
12	The technology disregards my wishes.
13	The technology lets me stay in control.
14	I feel subordinate to the technology.
15	The technology can be overruled, even if my decision should be wrong.
16	The technology has absolute decision-making power.
17	The technology takes away the ability to learn from my mistakes.
18	The technology decides against my will.
19	The technology requires that I submit.
20	I can't overrule the decisions of technology.
21	The final decision is up to the technology, even if I don't want it to be.
22	To protect me, the technology is allowed to take control, even if it overrides my decisions.
23	The system restricts my freedom.
24	The system denies my personal skills.
25	The technology represents the final decision-making authority.
26	The choices of the technology are irreversible.
27	I can't get around the choices of technology.
28	The technology forces me to accept its decisions.

3.3.4 Study II.4: Calibration study

To determine the potential underlying dimensions, we conducted a calibration study based on the 28 remaining items. We identified nine technologies (smart watch, smart phone, smart speaker, smart home systems, smart coffee machine, autocorrect function, autonomous car, smart thermostat, augmented reality [AR] glasses; for a details description see Table 8) that could potentially trigger TP by re-analyzing the interview materials and prior publications in the field. A total of 280 respondents (53% male, age: M= 40, SD = 12 years) were recruited via a professional online access panel in Germany for financial compensation (see Table 7).

Table 7: Descriptive analysis sample (Study II.4)

Sex	%	Age	in full years	Profession	%	Household net income p. a.	%
male	52.1	Min	18	Full-time employed	59.6	less than 30.000 EUR	25.9
female	47.2	Max	60	Working part-time	11.0	30.000 to 39.999 EUR	15.2
others	0.7	Average	39.93	Self-employed	4.3	40.000 to 49.999 EUR	17.7
		Median	39	Unemployed	5.3	50.000 to 59.999 EUR	9.6
		SD	12.30	Retired / pensioned	3.2	60.000 to 69.999 EUR	10.3
				School / Study	11.7	70.000 to 79.999 EUR	6.0
				in training	1.1	80.000 to 89.999 EUR	5.0
				Other (unable to work, etc.)	3.9	90.000 to 99.999 EUR	4.3
						more than 99.999 EUR	6.0

Note: N=282

Since technologies can only be perceived as paternalistic if consumers have some knowledge about them, respondents first rated their knowledge of all nine technologies. Of those technologies rated on the scale midpoint or above, a lottery algorithm randomly chose one as the target technology for the remainder of the survey. This dynamic assignment of technology to each respondent was a key reason for using an online survey. Next, the 28 items were shown with a focus on each respondent's target technology (with an explanation of the technology beforehand). Consumers were asked to rate each item on a 7-point Likert scale. We provided several variables to assess nomological validity and demographic variables.

Table 8: List of smart technologies used (Studies II.4 and II.5)

Technology	Explanations for survey participants
Smartwatch	A smartwatch is an electronic wristwatch that has additional sensors, actuators (e.g., vibration motor), and computer functionalities and connectivity. A key feature of smartwatches is that, in addition to the time, other information can be displayed, and the user can individually upgrade additional functions via programs ("apps"). Example of use: The sensor technology makes it possible to detect anomalies, which allows, for example, the use for elderly people (fall detection, assistance, epilepsy), in vulnerable workplaces or medical applications. Smartwatches are also used to detect cardiac arrhythmias, such as atrial fibrillation. Since 2019, there has also been a model that can measure blood pressure.
Smartphone	A smartphone is a cell phone with extensive computer functionalities and connectivity. Key features are touchscreens for operation and computer-like operating systems. Internet access is possible either via a mobile broadband connection from the mobile network provider or via WLAN. Example of use: Activity trackers not only enable health data to be monitored and stored but also enable this data to be forwarded to third parties, such as doctors. This is a form of self-disclosure that the sender of the data cannot escape if they use the device and are online.
Smart speaker	A smart speaker is a speaker connected to the internet that wirelessly transmits music or speech and integrates the functions of an intelligent personal assistant (IPA) via non-intrusive voice control and voice recognition. These devices usually have powerful hardware that records voice commands using multiple microphones. This generates audio recordings that can be effectively processed on processing servers. Example of use: The IPA function is only triggered by an activation password. If the microphone function is active, the environment is constantly monitored on the device, and the last few seconds are recorded on the device. It is not apparent to the user how and to what extent the recorded information is processed. The recordings are not processed and stored in the device but at the corresponding provider.
Smart home systems	The term "smart home" refers to a home that is equipped with information and sensor technology and is networked both internally and externally. Related terms are "smart living" and "intelligent home." The aim is to improve the quality of life and living, operational and burglary security, and energy efficiency, which has both economic and ecological implications. Examples of use: Automatically controlled heating, ventilation, doors, windows, awnings, blinds, and lamps (building or home automation), as well as systems that can be controlled and manipulated manually via mobile devices such as smartphones are just as much part of the smart home as smart electricity meters.
Smart coffee machine	The term "smart coffee machine" is aimed at coffee machines that have been upgraded in terms of information and sensor technology. Smart coffee machines and espresso machines are more convenient to use, more adjustable to the user's wishes, and sometimes make tastier coffee than conventional coffee machines. However, the great thing about a smart coffee maker is that you can conveniently operate it remotely via app or voice (Alexa, Google Assistant) and create your own personal coffee variant or espresso, determining how much coffee, water and milk foam should flow into the cup and in what order.
Autocorrect feature in WhatsApp	Autocorrect is a typing help function in computer programs for typo and spelling correction. In addition, there are functions for automatically writing out abbreviations, word endings, and acronyms. Another function is the automatic insertion of special characters or automatic text formatting when special characters or character strings are entered.
Autonomous car	Autonomous driving is the locomotion of vehicles, mobile robots and driverless transport systems that behave largely autonomously. Example of use: The car acts autonomously and fully automatically. No driver or human intervention is required other than setting the destination and starting the system. The vehicle does not need a steering wheel or pedals and decides independently on speed and route selection without involving the driver in the decision-making process.
Smart thermostat	Intelligent thermostat models use networked door and window sensors to detect when a window is opened for ventilation and adjust their heating output accordingly. They can also be networked with a room climate sensor, with which they can then exchange information. Example of use: Presence detection by geofencing automatically detects when it is time to heat up again and warms up the home in good time. This works via the smartphone's GPS signal. When the user leaves the house or apartment, the smart heating system reduces the temperature and vice versa.
Augmented-reality glasses	Augmented reality (AR) is the computer-based extension of reality perception. This information can address all human sensory modalities. With the help of data glasses ("head mounted displays"; HDMs), this technology can be used while the hands are free for any activities. Example of use: The repair or maintenance of machines can be complex and require special expertise. AR enables easy solution finding and knowledge transfer for future service cases. Instructions are given by an expert to the service employee, technician, customer, or business partner. The expert takes the view of the technician or customer via the data glasses. Assistance is provided by means of a video call and virtual elements, such as drawings, symbols, or short messages.

Following established procedures in the literature (Churchill, 1979; DeVellis, 2017), we applied EFA to the 28 items. A three-factor solution (see Table 9) was deemed most appropriate based on four criteria: eigenvalues were greater than one, a parallel analysis suggested a three-factor solution, a minimum average partial test suggested a three-factor solution (Velicer, 1976), and the interpretation of the factors was possible and plausible. To better understand the factor structure and improve the measurement characteristics, we examined the factor structure using a principal axis analysis with oblique promax rotation. We eliminated items with low factor loadings (<│0.50│) and/or problematic cross loadings (>│0.30│) as suggested in the literature (Hair et al., 2019). The final solution consisted of 16 items and explained 59.61% of the total item variance.

Table 9: EFA results (Study II.4)

Items	Limiting user freedom	Lack of overruling prospects	welfare intention by technology
The system restricts my freedom.	**.877**	-.052	-.033
The technology overrides my desires.	**.795**	-.060	.135
The technology makes me lose freedom of choice.	**.783**	.014	.071
The technology disregards my wishes.	**.784**	.095	-.081
The technology decides against my will.	**.777**	.012	.018
I feel like I'm externally controlled by the technology.	**.675**	.097	-.089
The technology is authoritarian.	**.620**	.179	.001
The final decision is up to the technology, even if I don't want it to be.	-.054	**.854**	.052
I can't overrule the decisions of technology.	.030	**.787**	-.011
I can't get around the choices of technology.	.055	**.733**	-.008
The technology forces me to accept its decisions.	.197	**.650**	-.007
The technology requires that I submit.	.255	**.607**	-.047
The technology ensures that I follow rules.	.010	-.141	**.780**
The technology ensures that I follow regulations, even if I didn't intend to.	.194	-.041	**.647**
The technology wants the best for me, even if that means overruling me.	-.057	.046	**.613**
To protect me, the technology is allowed to take control, even if it overrides my decisions.	-.157	.341	**.566**
Cronbach's alpha	.918	.895	.766
Lowest corrected item-to-total correlation	.672	.722	.539
Mean	3.11	2.81	3.38
SD	1.35	1.35	1.23
Factor correlations			
Lack of overruling prospects	.709		
Welfare intention by technology	.390	.446	

Method: principal axis analyses, Promax rotation; loadings above .5 shown in bold; SD = standard deviation

Scale inspection

Reliability analyses showed sufficient alpha coefficients above 0.70 (Hair et al., 2019) for each dimension (see Table 9). The resulting factors were consistent with the theoretical definition of TP and the results of Study II.1. Therefore, we followed the definition of TP in naming the extracted dimensions: limiting user freedom, lack of overruling prospects, and technology welfare intention. The measure of sampling adequacy was 0.928, exceeding the minimum criterion of 0.50 (H. F. Kaiser, 1974). Bartlett's test for sphericity was significant at the <0.001 level (Hair et al., 2019). To test robustness, replications using different estimators (e.g., maximum likelihood) and rotation methods (e.g., varimax) yielded similar results. A series of replications based on different subsamples (e.g., gender or age) demonstrated robustness.

3.3.5 Study II.5: Validation study

While Study II.4 provides preliminary evidence regarding the factorial structure, the measurement tool had not yet been replicated and validated in a different setting. Thus, in line with recommendations in the literature (Hair et al., 2019), Study II.5 aimed to validate the factor structure using CFA and investigate discriminant validity and nomological validity.

In Study II.5, we used the same sampling and survey procedure as in the calibration study (N = 323; 54% males, age: M = 42, SD = 13 years; details see Table 10). No respondents of Study II.4 were part of this data collection. The questionnaire included the TP items identified in Study II.4. Furthermore, to assess nomological validity, we included established scales from the literature, namely performance expectancy (the degree to which using a technology will provide utilitarian benefits to consumers in performing certain activities; synonym: PU) and effort expectancy (the degree of ease associated with consumers' use of technology; synonym: ease of use; Venkatesh et al., 2012). Furthermore, we included two theoretically unrelated variables, internal political efficacy and metaverse knowledge, for common method variance (CMV) tests. All items are listed in Table 34 in the appendix.

Table 10: Descriptive analysis sample (Study II.5)

Sex	%	Age	in full years	Profession	%	Household net income p. a.	%
male	53.7	Min	18	Full-time employed	54.3	less than 30.000 EUR	63.2
female	45.4	Max	60	Working part-time	13.5	30.000 to 39.999 EUR	10.1
others	0.9	Average	41.54	Self-employed	6.1	40.000 to 49.999 EUR	6.7
		Median	43	Unemployed	4.3	50.000 to 59.999 EUR	6.7
		SD	12.54	Retired / pensioned	5.5	60.000 to 69.999 EUR	3.4
				School / Study	8.6	70.000 to 79.999 EUR	3.7
				in training	1.5	80.000 to 89.999 EUR	2.5
				Other (unable to work, etc.)	5.8	90.000 to 99.999 EUR	1.8
						more than 99.999 EUR	1.8

Note: N = 323

Fit validity, reliability, convergent and discriminant validity, and robustness

On a global level, the CFA (AMOS, ML estimation) indicated a good model fit (see Table 13; $\chi 2 = 233.733$; df = 101.00, $p < 0.001$; $\chi 2/df = 2.314$; comparative fit index = 0.963, Tucker–Lewis index = 0.957, root mean square error of approximation = 0.064 [0.053; 0.075], standardized root mean square residual = 0.058). All factor loadings were significant ($p < 0.001$) and in the proposed direction (Table 13). Composite reliabilities all met the benchmark of 0.70 (Hair et al., 2019). All AVE values were above the threshold of 0.50, reflecting adequate convergent validity (Hair et al., 2019). For discriminant validity, the model met the Fornell-Larcker criterion (Fornell & Larcker, 1981) and the HTMT threshold (see Table 11), confirming the three-factor solution (Henseler et al., 2015).

Table 11: Fornell-Larcker criterion and HTMT results (Study II.5)

Fornell-Larcker Criterion			
Study II.5			
Factor	1	2	3
1	.837		
2	.591*	.824	
3	.210*	.371*	.738
HTMT results			
Factor	**1**	**2**	**3**
1			
2	.612		
3	.224	.371	

Note: Significance of correlations: * $p < 0.001$

We tested the robustness of the model by performing invariance tests for age and gender, with no variance between groups (Putnick & Bornstein, 2016). In all cases, the χ^2 difference tests were insignificant, meaning there was no variance between subgroups (see Table 12). We further applied several established tests for common method variance and controlling for marker variables, which all indicate no concerns (see Table 36 and Table 37 in the appendix).

Table 12: Measurement invariance tests for age and gender (Study II.5)

Model	X^2 (*df*)	CFI	RMSEA (90% CI)	PCLOSE	Model comparison	LR of ΔX^2 (*df*)	ΔCFI	ΔRMSEA	ΔPCLOSE
Age_high vs age_low									
M1: configural invariance	365.590* (202)	.956	.050 (.042; .058)	.490	-	-	-	-	-
M2: metric invariance	376.119* (215)	.957	.048 (.040; .056)	.643	M1	10.529 (13); p = .650	.001	.002	.153
M3: scalar invariance	395.427* (228)	.955	.048 (.040; .055)	.684	M1	29.837 (26); p = .247	.002	.000	.041
Male vs female									
M1: configural invariance	362.900* (202)	.956	.050 (.041; .058)	.504	-	-	-	-	-
M2: metric invariance	377.361* (218)	.956	.048 (.040; .056)	.671	M1	14.461 (16); p = .564	.000	.002	.167
M3: scalar invariance	386.546* (237)	.958	.044 (.036; .052)	.878	M1	23.646 (35); p = .928	.003	.006	.374

Note: age_high n = 168; age_low n = 158 (N = 326; no missing values); male n = 175; female n = 148 (N = 326); * = p < .000; LR = likelihood ratio test

Table 13: CFA results (Study II.5)

	Study II.5
Global model	
$\chi2$ (df)	233.733 (101)
$\chi2$/df ratio	2.314
TLI	.957
CFI	.963
RMSEA (LO90/HI90)	.064 (.053;.075)
SRMR	.058
Autonomy cut	
CR	.943
AVE	.703
The system restricts my freedom.	.841
The technology makes me lose freedom of choice.	.838
The technology overrides my desires.	.908
The technology disregards my wishes.	.855
The technology decides against my will.	.878
I feel like I'm externally controlled by the technology.	.780
The technology is authoritarian.	.761
Overruling options	
CR	.913
AVE	.678
The final decision is up to the technology, even if I don't want it to be.	.833
I can't overrule the decisions of technology.	.827
I can't get around the choices of technology.	.807
The technology requires that I submit.	.794
The technology forces me to accept its decisions.	.857
Welfare intention	
CR	.827
AVE	.546
The technology ensures that I follow rules.	.777
The technology wants the best for me, even if that means overruling me.	.712
The technology ensures that I follow regulations, even if I didn't intend to.	.799
To protect me, the technology is allowed to take control, even if it overrides my decisions.	.659

Note: Estimator: maximum likelihood; all factor loadings are significant (all p < .001); Abbreviations: CFI: Comparative fit index; TLI: Tucker–Lewis index; RMSEA: root mean square error of approximation; SRMR: standardized root mean square residual.

3.3.6 Assessment of nomological validity

Nomological validity is given when a construct shows expected associations in a network of related variables (Bagozzi & Yi, 2012). We tested nomological validity by investigating the empirical relationships of TP with a related construct, an antecedent, and consequences (see Table 4 for theoretical motivation). All data used for these nomological tests were gathered in Studies II.4 and II.5. All items were translated into German. The identified correlational patterns are in line with theoretical assumptions and therefore support nomological validity (see Table 14).

As postulated, product autonomy can be interpreted as an antecedent, as it was positively correlated with all sub-dimensions and TP. We explored the roles of age and gender, two common variables in technology acceptance research. The results indicated that paternalism was uncorrelated with age and gender, suggesting that paternalism can be experienced across groups. This is plausible, yet the underlying mechanisms might differ (e.g., rebellion for younger consumers with stronger needs for autonomy versus older users with more lived experience resulting in more confidence in their own capabilities); testing this remains an avenue for future research. An additional t-test for equality of means comparing gender showed similar results, with males and females experiencing equivalent levels of TP in both, Study II.4 and II.5 (see Table 15).

Table 14: Correlations between TP, antecedents, related constructs, and consequences (Studies II.4 and II.5)

Antecedents, related constructs, consequences	Study	Limiting user freedom	Lack of overruling prospects	Welfare intention by technology	Technology Paternalism
Antecedents					
Product autonomy (Rijsdijk et al., 2007)	4	.403***	.387***	.464***	.505***
Age	4	.070	.025	-.043	.023
Age	5	-.009	.005	.045	.016
Gender	4	.061	.033	-.010	.036
Gender	5	.048	.043	.095	.080
Related constructs					
Technology intrusiveness (Mani & Chouk, 2017)	4	.703***	.483***	$.115^{T}$	.537***
Consequences					
Perceived usefulness (adapted from Davis, 1989)	4	-.234***	-.151*	.175**	-.094
Effort expectancy (Venkatesh et al., 2012)	5	-.383***	-.233***	.002	-.279***
Performance expectancy (Venkatesh et al., 2012)	5	-.329***	-.062	.149**	-.118*

Note: Pearson correlations; significance of correlations: *** p<.001; ** p <.01; * p <.05; ^{T} p<.10

*Table 15: T-test for equality of means (Studies II.4 and II.5); Gender*TPS (and its dimensions)*

Levene's test for equality of variances			t-test for equality of means						
	F	Sig.	T	df	Sig.	Mean diff.	Std. Error diff.	95% CI	
Study II.4									
Limiting user freedom	2.370	.125	1.026	278	.306	.166	.162	-.153	.485
Lack of overruling prospects	.679	.411	.547	278	.584	.089	.162	-.230	.408
Welfare intention of technology	.012	.912	-.163	278	.870	-.024	.147	-.314	.266
TPS	2.525	.113	.593	278	.554	.077	.130	-.178	.332
Study II.5									
Limiting user freedom	.319	.573	.856	321	.392	.139	.163	-.181	.459
Lack of overruling prospects	.247	.619	.775	321	.439	.127	.164	-.196	.450
Welfare intention of technology	2.386	.123	1.708	321	.089	.246	.144	-.037	.529
TPS	.318	.573	.573	321	.154	.171	.119	-.064	.406

Note: Sig. = two-tailed significance

The relationship between TP and technology intrusiveness, where intrusion refers to entrance into the consumer's life without permission (Mani & Chouk, 2017), showed robust correlational evidence, and technology intrusion was found to be a strongly related concept. Scales representing the postulated consequences of TP, namely PU, EE, and PE, showed negative correlational relations to TP. In conclusion, these results indicate nomological validity. Following MacKenzie, & Podsakoff, (2011), our final step was to develop norms (calculating means and standard deviations) to aid in the interpretation of scores on the scale (see Table 35 in the appendix).

3.4 Discussion

Smart products have become an integral aspect of our daily routines, offering undeniable benefits such as heightened efficiency and convenience. While these advantages are pivotal, they alone fall short of fully elucidating consumer behaviors, attitudes, and the adoption of technology (Chitturi et al., 2008). Despite augmenting efficiency, these features may encounter resistance or diminished acceptance (Rochi, 2023). Existing research indicates that consumers favor smart technologies owing to their superior capabilities (e.g., Porter & Heppelmann, 2014). Nevertheless, scholars have demonstrated that these capabilities can provoke resistance, impacting user well-being (e.g., Su et al., 2014 and Vimalkumar et al., 2021). This study delves into the concept of paternalism within human-computer interaction, specifically exploring TP. Through a series of five studies, we identified three fundamental dimensions of TP along with the overarching measurement scale designed to quantify TP. All three subscales and the measurement scale exhibit anticipated correlations within a nomological network that encompasses TP's antecedents, related concepts, and consequences of TP, affirming the scale's reliability. This contributes to both theoretical and practical domains, providing valuable insights into the multifaceted nature of TP.

3.4.1 Theoretical contributions

First, previous research on TP has been mostly conceptual in nature (Hilty, 2015; Kinder et al., 2008; Millar, 2015; Spiekermann & Pallas, 2006) or used ad hoc scales (e.g., Schein & Rauschnabel, 2022). Despite highlighting the importance of TP, these studies lack rigorous empirical support. This is not surprising given the lack of systematic scale construction. While scholars have emphasized the impact of product attributes on consumers' adoption (e.g., M. Li et al., 2023), insufficient attention has been given to the concept of TP. Addressing this gap, our work presents a well-grounded and practical conceptual framework for understanding technology's potential to exert paternalism over users. By using a mixed-methods approach, we contribute to and extend prior marketing research.

Second, our work enhances the evolving field of research that centers on emerging technologies within the marketing domain. Several investigations have indicated the impact of artificial intelligence (e.g., Puntoni et al., 2021) and heightened product autonomy (e.g., Formosa, 2021 and Lucia-Palacios & Pérez-López, 2021) on product adoption. Furthermore, studies have shown that consumer resistance toward product automation tends to arise when opportunities to override functions are limited (Millar, 2015; Sørensen & Schmidt, 2016; Venkatesh, 2022). We add to this stream of research by operationalizing TP comprising three first-order dimensions. This offers a robust 16-item measurement tool for TP, serving researchers in human-computer interaction, management information systems, marketing, and related fields, and enabling the pursuit of consistent research outcomes in the area of smart technology adoption across diverse fields of study. It enables researchers to collect reliable and valid data, which is essential for conducting meaningful empirical studies on TP. This enhances the quality of research in the field and helps build a more robust knowledge base. We echo with Spiekermann and Pallas (2006) that product autonomy is a highly relevant construct in the field of TP. However, while Spiekermann and Pallas (2006) discuss it as a dimension, we conceptualize it as an antecedent, and challenge the assumption "the more support the better" of established theories (like TAM).

Third, we provide empirical evidence for the TP–technology adoption relationship and broaden the understanding of whether TP affects smart technology acceptance. We have provided preliminary empirical evidence for associations between TP and an antecedent (product autonomy; Rijsdijk et al., 2007), a related construct (product intrusiveness; Mani & Chouk, 2017), and consequences (e.g., effort expectancy and performance expectancy; Venkatesh et al., 2012). Overall, this emphasizes the relevance of TP in technology research.

3.4.2 Managerial implications

Notwithstanding the distinct advantages offered by smart products, this innovative technology appears to possess attributes that could impede its widespread adoption (de Bellis et al., 2023). The advent of smart, interconnected products enables companies to forge novel connections with customers, but also demands fresh approaches to marketing strategies (Porter & Heppelmann, 2014). First, to market smart products successfully, it is necessary to consider perceived TP when developing these products. The study results reveal that TP significantly affects technology adoption and offer important implications that may advance managerial thinking about TP. Our validated measurement scale enables product developers to assess the paternalistic potential of their smart products. For example, finding an equilibrium between providing supportive information and patronizing users with overwhelming information provision is key for future smart product development. This is helpful when developing AI-based measurement tools for TP to determine the optimal degree of information input, autonomy cutting, and potential for overruling actions and creating more adaptive, less paternalistic smart products.

From a governmental perspective, this scale can be supportive in finding the optimal degree of adjustment to rules or laws. It can help establish how strong the perceived degree of TP should be to ensure certain user behavior and increase general safety (e.g., in traffic). This also holds true for rolling out new technologies in companies, such as AR-supported smart glasses in warehousing (Schein & Rauschnabel, 2021) or in the vast area of digitization in healthcare (Renner & Moszeik, 2023). Marketers dealing with intelligent products can utilize these findings to shape their segmentation and positioning strategies. One approach to leveraging our conclusions is to categorize consumers based on their varying levels of TP perception, thereby presenting distinct categories of smart products to these groups.

3.4.3 Limitations and future research

As with any research, this study has some limitations that suggest avenues for new research opportunities. First, this work is based on self-reported correlational data from a single cultural and national setting. Follow-up studies based on our scale may result in significant contributions to the existing body of knowledge, for instance, by comparing results from different cultural environments. Studies assessing strategies to reduce TP can contribute to users' overall well-being, increasing product acceptance. It would also be beneficial to understand how different combinations of the three dimensions lead to differential behavioral outcomes or degrees of TP. It would be informative to understand how the single dimensions interact (especially whether a high score of welfare intention outplays the other dimensions) and how these dimensions affect TP from an isolated point of view.[8] Furthermore, identifying ways to measure TP based on physiological data and reducing it adaptively may add further knowledge on how TP affects user choices. On this, new technologies, such as specific AR or virtual reality devices, can have built-in sensors to capture such data across usage contexts (Au et al., 2023; Rauschnabel et al., 2022). Moreover, while this manuscript focuses on the perception of TP at the user level, it might be interesting to understand whether users realize that the real patrons behind paternalistic technologies are the developers, marketers, and governmental bodies who develop the underlying algorithms or introduce overarching paternalistic regulations. The integration of TP into established theories and related constructs, such as digitalization anxiety (Pfaffinger et al., 2021) could lead to important contributions in these fields.

[8] We thank an anonymous reviewer for this valuable suggestion.

CHAPTER

4

PAPER III

Technology paternalism: Mediating and moderating Effects

4. Paper III: Technology paternalism: Mediating and moderating effects[9]

Abstract

Daily advances in artificial intelligence are increasing the intelligence of technologies, from smart vacuum cleaners that help with household chores to smart cars that navigate urban landscapes. Traditional research on technology adoption suggests that increased functionality correlates with higher adoption rates, but this is not always true. As technologies become smarter, more context-aware, and more feature-rich, they may inadvertently act as protective entities to the user, much like a parent. This can lead to perceptions of technology paternalism, characterized by technology actions that restrict user freedom, are ostensibly in the user's best interest, and are difficult to override. In a series of correlational studies, the author finds lower adoption intentions and higher technology resistance associated with perceived technology paternalism. In addition, this research explores the potential moderators of its effects on technology adoption and resistance. The results present empirical evidence from mediation analyses that common marketing strategies such as human-like design and increased autonomy do not necessarily lead to higher adoption rates or lower technology resistance. Paternalistic product features are an issue of concern in practice, and marketers should be aware of the paternalistic potential of their products and adapt their strategies accordingly.

Keywords: technology paternalism, paternalism, smart technologies, technology adoption, technology resistance

[9] This chapter is an unpublished research manuscript authored solely by Martin Rochi. No co-authors were involved in this work prior to the submission of this dissertation. The formatting, content, and number of authors of this chapter may differ from any future published version.

4.1 Introduction

Smart devices have become indispensable in our daily lives, performing tasks from cleaning to transportation, such as autonomous vacuum cleaners (de Bellis et al., 2023) and autonomous taxis.[10] These products offer efficiency and convenience, operating autonomously to free users from unpleasant tasks. They outperform their traditional counterparts by adapting to new situations and interacting with users and other devices (Raff et al., 2020). The "cloudification" of potentially all everyday objects (Bronson, 2022) leads to an "Internet of Everything," a "network of connections between smart things, people, processes, and data with real-time data/information flows between them" (Langley et al., 2021, p. 853). This network allows the digitization of all our usage contexts, which helps smart devices understand them. To increase user adoption, smart product development seeks to both increase perceived functionality with increased autonomy, which is implemented through high context awareness of the products, and further enhance human-like attributes (like Amazon's Alexa), a concept termed "anthropomorphism." These strategies are supported by recent product adoption research. Technology adoption theories (e.g., Davis, 1989 and Venkatesh, 2000) emphasize that increasing product usefulness (through higher autonomy) can outweigh negative attributes and increase product adoption, and research suggests that making products more human-like increases product (Yuan & Dennis, 2019) and brand attachment (Ma et al., 2023) and leads to a more positive user–product interaction (Cornelius & Leidner, 2021; Luczak et al., 2003).

On the contrary, and as discussed in the previous chapters of this dissertation, when smart products are equipped with autonomous abilities, there is a danger of creating overly protective and excessively supportive products, leading to a user perception of technology paternalism (TP; Rochi, 2023; Rochi et al., 2024). TP is defined as an independent action undertaken by a technology, purportedly in the user's best interest, directly impacting them, perceived as limiting their freedom, and that cannot be overruled without sacrificing functionality (Rochi et al., 2024). Importantly, product autonomy is a necessary prerequisite for TP since intelligent technologies inherently operate autonomously or independently (Raff et al., 2020; Rochi et al., 2024).

[10] Cruise autonomous taxis, a subsidiary of General Motors, provides self-driving vehicles without the need for a human driver, mainly in San Francisco.

In the absence of autonomy, technology can only act on behalf of the user or perform actions initiated by the user, which excludes the occurrence of TP (Rochi et al., 2024).

Overprotective products that act without user consent and make decisions "over the user's head" can make users feel as though technology is treating them like a parent (Rochi, 2023; Rochi et al., 2024), which can lead to harmful behavior (Farh & Cheng, 2000) and counterproductive actions (Daniels & Jordan, 2019). Therefore, while a smart technology may have functional benefits and enhanced human-like features, understanding product adoption and resistance requires considering more granular components (Chitturi et al., 2008). These include social and emotional factors, such as how people psychologically value the smart product's function as an active social participant (Wirtz et al., 2018).

As "anthropomorphism entails attributing humanlike properties, characteristics, or mental states to real or imagined nonhuman agents and objects" (Epley et al., 2007, p. 865), this phenomenon plays a crucial role in technology adoption research (Laksmidewi et al., 2017; Yingzi Xu et al., 2020; M. Yang et al., 2023). Most research suggests that anthropomorphism is a way to increase product adoption. For instance, it reduces people's anxiety and stress, satisfies their social needs (Niu et al., 2018), promotes trust (Waytz et al., 2014), and enhances perceived enjoyment (Moussawi et al., 2021). Conversely, other (rarer) studies have found that anthropomorphism can also have negative effects on user adoption (Gursoy et al., 2019; Lin et al., 2020; L. Lu et al., 2019). Anthropomorphism may also elicit negative emotional responses (R. Fu & Xu, 2021), as giving products human characteristics may have negative consequences (Sætra, 2020). As more human-like attributes can increase the intensity of emotional responses in both negative and positive ways (Chandler & Schwarz, 2010; R. Fu & Xu, 2021), perceptual TP is more likely for anthropomorphic products. This is interesting because anthropomorphism is generally considered positive in marketing research (e.g., Epley et al., 2007; S. Kim & McGill, 2011).

Like anthropomorphism, product autonomy, which refers to a product's ability to operate independently without human input and effectively take control of itself (Rijsdijk & Hultink, 2003), is generally considered positive because it increases perceived usefulness (Formosa, 2021; Lucia-Palacios & Pérez-López, 2021). However, it can also have negative consequences, such as reduced personal autonomy, leading to increased perceptions of complexity and risk, which can reduce consumer satisfaction (Rijsdijk & Hultink, 2003, 2009).

As a result, greater product autonomy could increase perceptions of various dimensions of TP, such as limited override options or perceived threats to freedom (Rochi, 2023; Rochi et al., 2024).

On the one hand, anthropomorphic and highly autonomous products increase product acceptance, but on the other hand, both increase TP, which in turn negatively affects product acceptance. This double-edged effect should be investigated to understand under which circumstances the above-mentioned strategies in product development can lead to negative rather than positive results. This study addresses this gap by investigating the impact of TP on technology adoption and the mediating roles of product autonomy and anthropomorphism in this dynamic. The results from three consecutive studies show how users react to potentially paternalistic technologies by examining two different dependent variables: behavioral intention and technology resistance. In addition, human-like product attributes and product autonomy influence behavioral intention and resistance while also influencing perceptions of TP. This creates a competitive relationship: increasing human-like attributes and autonomy increases TP, which subsequently decreases behavioral intention and increases resistance. Exploratory moderation analyses show that emphasizing domain-specific innovativeness, product involvement, and product experience mitigates the negative impact of TP on behavioral intention and resistance.

These findings represent a significant contribution to the field, as they mark one of the first empirical explorations of the impact of TP on behavioral intention and technology resistance. They shed light on why traditional product acceptance theories may not be sufficient in the context of potentially paternalistic smart products. Understanding how users make acceptance decisions with smart products and how TP is developed in this context is critical for researchers in order to move beyond traditional theories and enrich our understanding of users' perceptions of smart products. Moreover, these findings have implications for retail practice, cautioning against common strategies aimed at enhancing human-like features and autonomy that may inadvertently lead to TP-related drawbacks.

The remaining sections of this manuscript are organized as follows: Section 4.2 presents the theoretical underpinnings and hypothesis development for the three successive studies. Section 4.3 describes the research methodology, the data analysis approaches, and the results of each study. This is followed by a comprehensive discussion in Section 4.4, in which the author addresses the implications of the findings, including their theoretical and practical contributions, as well as acknowledging limitations and suggesting potential avenues for future research in this area.

4.2 Theoretical background and hypotheses

4.2.1 Smart products

In academia, the term “smart product” has not yet been consistently defined. While the term “smart” is often employed interchangeably with various concepts, such as “intelligent,” “clever,” or simply “advanced,” the concept of a “smart product” encompasses much broader implications (Tomiyama et al., 2019). Academics have used several definitions to describe smart products: Kahle et al. (2020, p. 2) described this type of product as an artifact that “besides its physical components, contains digital technology – in the form of, for example, sensors, software and micro-chips – and therefore has capabilities to collect, monitor, control and optimize data from different sources and that may also interact with other products and perform tasks without human input.” Abramovici (2014) defined them as cyber-physical systems that further incorporate and utilize internet-based services to fulfill their intended functions. The cyber-physical component of this definition was also underlined by Pardo et al. (2020), who stated that a smart product consists of a physical and a digital part, where the smart product is a physical product in the first place, which means that it has to address usage on its own. Raff et al. (2020) defined these products as devices capable of learning, anticipating, and acting independently of user interventions. In this manuscript, the author combines the definitions of Pardo et al. (2020) and Raff et al. (2020) and defines smart products as those consisting of a physical and a digital part, with the ability to learn, anticipate, and act independently of user interventions.

4.2.2 Technology acceptance and resistance

Research on technology adoption has garnered considerable attention in efforts to elucidate the reasons for and mechanisms underlying user acceptance of new technologies. Particularly within the field of information systems, technology adoption has emerged as a prominent area of study. Defined as a sociological model describing the acceptance of new products or innovations (Yongjun Xu et al., 2021), technology adoption research aims to understand, predict, and elucidate the factors influencing adoption behavior at the individual and organizational levels. These endeavors have contributed to the development of conceptual models and frameworks elucidating the relationships between these variables and adoption behavior, such as TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003). Both models include several factors that influence adoption intention, for instance, perceived usefulness (TAM), performance expectancy (UTAUT), perceived ease of use (TAM), and effort expectancy (UTAUT), where performance expectancy is similar to perceived usefulness and effort expectancy is similar to perceived ease of use (Venkatesh et al., 2003).

Comparatively less attention has been given to individuals' resistance to technologies and their subsequent use (H.-W. Kim & Kankanhalli, 2009; Lapointe & Rivard, 2005). Resistance has not been consistently defined in recent literature. One definition describes it as "a person's proactive intention to resist using a technology" (Schein & Rauschnabel, 2021, p. 3346). Alternatively, Raff et al. (2024, p. 3) wrote, "In contrast to acceptance, which represents factual behavior, resistance can be understood as a cognitive force that precludes such behavior." Unlike acceptance, which manifests as actual behavior, resistance acts as a mental barrier against using a product (Bhattacherjee & Hikmet, 2007; H.-W. Kim & Kankanhalli, 2009). In a more granular definition, Talke and Heidenreich (2014, p. 898) defined active resistance as "an attitudinal outcome that follows an unfavorable evaluation of a new product." Resistance to innovation is a significant aspect of consumer behavior, equally pivotal as acceptance and adoption (Talwar et al., 2020). There is a notable deficiency in research on the determinants that lead to the outright rejection of technology (Venkatesh & Brown, 2001) and no consensus on what constitutes user resistance (Laumer & Eckhardt, 2012). The field of technology resistance seeks to understand why individuals decide against using technologies (Lapointe & Rivard, 2005). This line of inquiry is based on the concept that individuals naturally strive for psychological equilibrium (Heider, 1958; Newcomb, 1953; Osgood & Tannenbaum, 1955). According to studies on resistance, any technology imposed upon individuals can threaten this balance, leading them to resist change to avoid the unsettling process of adapting to new conditions (Talke & Heidenreich, 2014).

To understand resistance, one must consider how inhibitors of resistance interact with enablers of adoption that are usually present, even in the case of resistance (Cenfetelli, 2004; Cenfetelli & Schwarz, 2011). Inhibitors take on a predominant role in the adoption process (Cenfetelli, 2004), as "bad is stronger than good" (Baumeister et al., 2001) and "losses loom larger than gains" (Kahneman & Tversky, 1979). These inhibitors can directly and indirectly impact adoption intentions (Cenfetelli, 2004; Cenfetelli & Schwarz, 2011). Certain inhibitors like fear of job loss (Spreer & Rauschnabel, 2016), loss of routine (Spreer & Rauschnabel, 2016), privacy concerns (Hsu & Lin, 2018), and loss of competence (Schein & Rauschnabel, 2021) are common across various technologies, yet many barriers remain unique to specific technologies (Bhattacherjee & Hikmet, 2007; Craig et al., 2019), evolving alongside the technologies themselves (Raff & Wentzel, 2018).

Hence, resistance should not be equated with low acceptance; a lack of acceptance may simply indicate user indifference toward a technology rather than active opposition, such as when users fail to perceive its utility. Significant resistance might lead individuals to avoid using a technology – even when they recognize its benefits, such as in task automation – due to concerns like job security (Schein & Rauschnabel, 2021). Consequently, resistance and acceptance should not be seen as diametrically opposed.

4.2.3 Technology paternalism

Paternalism is a widely recognized occurrence within the realm of interactions involving individuals or governments. In this context, paternalism is described as "the interference of a state or an individual with another person, against their will, and defended or motivated by a claim that the person interfered with will be better off or protected from harm" (Dworkin, 2020, para. 1). From the viewpoint of an individual who is the recipient of paternalism, this behavior may be seen as personally harmful (Farh & Cheng, 2000), potentially prompting them to take counterproductive actions (Daniels & Jordan, 2019). Within a family context, parents often make decisions in a paternalistic manner for their children, such as choices related to homework or television consumption. Despite their good intentions, situations may arise where the child feels like they are being overly controlled due to differing preferences. Paternalism can also be observed in several forms in the interactions between economically active organizations and their employees, as seen in labor control or industrial safety situations (Kinder et al., 2008), or between individuals and governments (Thaler & Sunstein, 2009).

Paternalistic dynamics can also become apparent in interactions with smart products when these objects have the capability to sense and differentiate between what is deemed appropriate and what is not, and then proceed to restrict or admonish people's actions based on this information (Spiekermann & Pallas, 2006). Despite TP being conceptually described almost twenty years ago by Spiekermann and Pallas (2006), relatively less scientific work has focused on this phenomenon in recent years. The first attempt to empirically analyze the effects of TP on consumer intentions (with an ad hoc scale) was made by Schein and Rauschnabel (2021), who showed a positive (negative) correlation between TP and technology resistance (technology acceptance). Underlining the importance of this topic, Rochi (2023) was the first to embed the concept of TP in a framework with technology adoption and resistance, formulating propositions on the effects of TP. Based on this work, Rochi et al. (2024) developed a measurement scale for TP and provided the first empirical evidence for how TP affects the technology adoption behavior of users. This supported the findings of Wirtz et al. (2018) that users' receptiveness to smart technologies can be impacted by social and emotional factors, including how they psychologically assess the product's role as a social entity actively engaging in their daily lives.

Limiting user freedom

Smart products can lead us to decrease our autonomy competencies and make our autonomy more vulnerable (Formosa, 2021). TP, as noted by Rochi (2023), can lead users to sense a loss of freedom or a perceived threat to their behavior, prompting efforts to restore this behavioral freedom, often through resistance. In support of this idea, Ogbanufe and Gerhart (2022) demonstrated a positive correlation between freedom restriction by smart wearables and perceived intrusiveness. For instance, if an autonomous car acts against a user's wishes, it can evoke feelings of autonomy being in jeopardy. Consequently, users might attempt to overturn the decision to regain their freedom. However, if regaining freedom proves challenging due to technical constraints or predefined settings, it can result in a revised product evaluation, potentially leading to reduced adoption intentions or increased resistance (Rochi, 2023).

Overruling the technology

Smart products are engineered to deliver value to consumers through autonomous action and self-execution of tasks (Behmann & Wu, 2015; Michler et al., 2020). When consumers interfere with the actions of smart products, they may forfeit value and functionality. Nevertheless, it is important to carefully design interventions to encourage the adoption and utilization of information technology (Venkatesh, 2022). In cases where altering or deactivating a smart product's functionality is not easily achievable, perhaps due to the need for specialized knowledge like programming skills, it can establish a paternalistic dynamic between the consumer and the device (Millar, 2015; Sørensen & Schmidt, 2016), resulting in increased resistance or decreased behavioral intention (Rochi, 2023).

Welfare intentions behind technology actions

Smart products are designed with the objective of enhancing user well-being, for instance, by serving as autonomous shopping assistants and recommendation agents that aim to reduce the time and costs associated with searching. While these algorithms ensure that users receive a manageable volume of pertinent and engaging information, they have the potential to compromise individual and independent decision-making processes (Appelgren, 2018, 2019; Helbing et al., 2019). This is because they may deprive users of potentially important decision-making information, limit their opportunities to broaden their knowledge, and curtail the perception of personal freedom in choice, ultimately leading to reduced usage (G. Lee & Lee, 2009; Weiser et al., 2016) due to increased resistance or dampened adoption intention. The dimension of welfare intention is of particular significance in understanding TP. Without a welfare intention, an action taken by a smart product cannot be perceived as paternalistic. In such cases, potential threats to freedom or a lack of options for overruling may be seen as mere cuts in autonomy. Therefore, a pivotal element of paternalism lies in the intention to promote user welfare in actions that involve overriding or threatening freedom.

In summary, the perception that a technology is paternalistic, as it diminishes user autonomy while purporting to act in the user's best interest, influences technology adoption intentions or resistance. This notion is supported by research demonstrating that the construct of technological paternalism correlates as expected with related factors such as technology intrusiveness, antecedents like product autonomy, and outcomes like perceived usefulness and performance expectancy. Additionally, Schein and Rauschnabel (2021) illustrated that the perception of paternalism in augmented reality glasses in a warehousing setting was negatively (positively) associated with technology acceptance (resistance). Feeling paternalized may lead to counterproductive behavior in human–smart product interactions, resulting in either increased resistance or decreased adoption intention. This sets the stage for the first two hypotheses:

H1a/b: TP negatively impacts consumer reactions to technologies, as reflected by (a) lower levels of acceptance and (b) higher levels of resistance.

4.2.4 Product autonomy as an antecedent of TP

For a technology to be perceived as paternalistic, it must operate autonomously (Rochi, 2023). Product autonomy pertains to the concept wherein a product operates independently without requiring human intervention, effectively taking charge autonomously (Rijsdijk & Hultink, 2003). When it comes to the role of product autonomy in shaping TP, the literature is inconsistent with regard to whether it is an antecedent or a dimension of TP. Spiekermann and Pallas (2006) included product autonomy as a dimension of their definition of TP, as "machines react automatically and autonomously which leaves recipients little room for anticipation or reaction" (Spiekermann & Pallas, 2006, p. 10). Rochi (2023) included product autonomy as a dimension of TP in his conceptual framework of the effects of TP on resistance and technology adoption. Conversely, Rochi et al. (2024) further developed the definition of TP and viewed product autonomy as an antecedent of TP, given that intelligent technologies inherently operate autonomously or independently (Raff et al., 2020). Without such autonomy, technology is limited to acting as an agent for the user or executing actions initiated by the user, thus excluding the possibility of TP. The author of this paper follows Rochi et al. (2024) and interprets product autonomy as an antecedent of TP.

Research suggests that product autonomy can increase adoption intention (Formosa, 2021; Lucia-Palacios & Pérez-López, 2021). Smart products can improve user experience and adaptability by collecting and analyzing extensive personal and contextual data (Karwatzki et al., 2017). Nevertheless, product autonomy can also lead to negative outcomes. Smart products often gather data discreetly or without explicit user approval, leading to concerns about diminished personal autonomy (Yost et al., 2019). Typically, overriding the autonomous functions of smart products is not straightforward without specialized knowledge, contributing to perceptions of TP (Rochi, 2023). These issues can lead to potential drawbacks of product autonomy, such as complexity and perceived risk, which could reduce overall consumer appreciation (Rijsdijk & Hultink, 2003, 2009). Furthermore, smart products that act autonomously could strip consumers of valuable experiences (de Bellis et al., 2023).[11]

[11] This dichotomy, wherein product autonomy has a direct positive (negative) impact on behavioral intention (resistance), yet indirectly fosters technology paternalism, leading to an adverse (favorable) effect on behavioral intention (resistance), is reflected in the two hypotheses H2a and H2b.

Consequently, the author anticipates a direct relationship between the level of product autonomy and the incidence of TP. Smart products employ pervasive and concealed mechanisms to adjust to the user and their environment without explicit user approval. This is likely to engender a sense of autonomy threat and subsequently evoke reactance (Rochi, 2023). Hence, increased product autonomy affects several aspects of TP (e.g., fewer or no overruling prospects or a perceived threat of freedom), resulting in an increase in perceived TP. This leads to the following hypothesis:

H2a: Product autonomy serves as an antecedent of TP, influencing TP positively.

Autonomy offers several advantages for consumers. Generally, prior research has identified a positive correlation between autonomy and relative advantage (Rijsdijk & Hultink, 2003). Autonomous products assume tasks, allowing consumers to save time and effort for engagement in other activities (Lucia-Palacios & Pérez-López, 2021). Consequently, consumers may perceive autonomous smart products as devices that enhance their comfort and well-being, boost task fulfillment efficiency and effectiveness, or relieve them from unwanted tasks (Cronin, 2010; Leung et al., 2018). Autonomy includes the collection of private information, enabling the delivery of personalized and more valuable messages to users (Zeng et al., 2021) and enhancing the product's efficiency in performing requested tasks, thereby increasing its overall usefulness (Lucia-Palacios & Pérez-López, 2021). Smart products, unlike traditional ones, not only serve basic functions but also provide additional features through connectivity and intelligence attributes (X. Yang et al., 2009). These new attributes "enable an entirely new set of product functions and capabilities," such as autonomy (Porter & Heppelmann, 2014, p. 69), enabling products to aid consumers in achieving behavioral goals and meeting performance expectations (Meyer-Waarden & Cloarec, 2022), which positively influences consumers' adoption intentions (M. Li et al., 2023).

With regard to technology resistance, research indicates that psychological hurdles, such as loss of autonomy (Wilson et al., 2017), loss of control (Balta-Ozkan et al., 2013), disruption of peace of mind (Hong et al., 2020), and fear of job loss (Schein & Rauschnabel, 2021), increase resistance toward smart products. When smart products act autonomously without user consent, it is likely that these barriers will lead to an increase in technology resistance. It is important to note again that resistance and acceptance should not be seen as diametrically opposed (for details, see Section 2.2) and to recognize that factors hindering resistance may intersect with facilitators of adoption, which often exist alongside resistance (Cenfetelli, 2004; Cenfetelli & Schwarz, 2011). Therefore, the following hypothesis is proposed:

H2b/c: Product autonomy impacts consumers' reactions to technologies, as reflected by (b) higher behavioral intention and (c) higher technology resistance.

Hypotheses H2a, H2b, and H2c are in a state of tension. Product autonomy positively affects the perception of TP, which positively affects adoption intention and technology resistance. This is underlined by the statement of Rochi (2023, p. 9) that "the common assumption in technology adoption research of 'the more support, the better' no longer holds" in the context of smart products. Therefore, the author hypothesizes the following:

H2d/e: The positive effect of product autonomy on (d) behavioral intention and (e) technology resistance is competitively mediated by TP.

4.2.5 The effects of anthropomorphism on behavioral intention

Recent research has shown that anthropomorphic product attributes increase purchase intention (Laksmidewi et al., 2017; Yingzi Xu et al., 2020; M. Yang et al., 2023), while other findings have indicated that anthropomorphism may mitigate resistance to technology (Christoforakos & Diefenbach, 2023; Cornelius & Leidner, 2021). Individuals who perceive technical devices as companions tend to engage with them more positively (Cornelius & Leidner, 2021; Luczak et al., 2003). This leads to the following hypotheses:

H3a/b: Anthropomorphism impacts consumer reactions to technologies, as reflected by (a) higher levels of acceptance and (b) lower levels of resistance.

Product anthropomorphism exerts a significant influence on psychological responses, yielding varied outcomes. For instance, anthropomorphizing products fulfills consumers' need for connectedness, enhancing vitality and self-control (F. Chen et al., 2018). Wu et al. (2023) found that anthropomorphizing product characteristics positively influenced recycling behavior through affective and cognitive responses. Chandler and Schwarz (2010) observed that anthropomorphism transforms the emotional quality of an experience, creating a more positive and enjoyable relationship. However, anthropomorphism can also lead to negative emotional responses, particularly among individuals possessing high self-esteem (R. Fu & Xu, 2021). This suggests that, in specific circumstances, attributing human characteristics to products may lead to adverse outcomes, highlighting that assigning social clues or agency to a product shapes consumer behavior and psychological reactions in diverse ways, inducing both positive and negative emotions. Sætra (2020) argued that crafting technologies with human-like attributes can be regarded as a form of deception, as it prompts individuals to interact with technology in a manner typically reserved for genuine human-to-human relationships. When users interact with smart products in a human-to-human manner, they may be more likely to experience feelings of paternalism. This leads us to the following hypothesis:

H3c: Anthropomorphism serves as an antecedent of TP, influencing TP positively.

Anthropomorphism of products increases users' emotional responses (Whillans et al., 2020). Interacting with anthropomorphic consumer products that exhibit human-like characteristics has the potential to fulfill social needs, at least partially (Mourey et al., 2017). Qiu and Benbasat (2009) showed that anthropomorphism can restore needs, such as the need for connectedness, and that human-like attributes influence users' perceptions of social presence. Hence, the author hypothesizes that anthropomorphism can increase the perception of TP as an emotional response to human-like product attributes, which in turn may negatively affect overall behavioral intention.

H3d/e: The (d) positive effect of anthropomorphism on behavioral intention and the (e) negative effect of anthropomorphism on technology resistance are competitively mediated by TP.

4.3 Research methodology and data analysis

We assessed the theorizing above with three consecutive studies. Study III.1 was designed as a panel survey to explore the direct impact of TP on behavioral intention. It investigates the influence of anthropomorphism and product autonomy on behavioral intention and TP. Study III.2 validates some of the results of Study III.1 (the relations of TP with anthropomorphism and product autonomy) and examines the effect of TP on technology resistance. Additionally, to augment the results of Study III.2, the author assessed several potential moderation effects of consumer attributes on the effect of TP on technology resistance. Study III.3 sheds light on how certain product attributes (paternalistic and human-like attributes) affect the effects examined in Studies III.1 and III.2.

4.3.1 Study overview

Three separate studies were carried out to test the developed hypotheses, as outlined in Section 4.2. The first study (Study III.1) examines both the direct effects of TP on behavioral intention and how the perception of anthropomorphism and product autonomy affects adoption intention and TP. Additionally, how product autonomy and anthropomorphism shape the perception of TP is examined. In addition to replicating some of the results from Study III.1 with a new sample, Study III.2 examines the effects of anthropomorphism, product autonomy, and TP on technology resistance. It also includes an exploratory moderation analysis of the potential moderating constructs of the relationship between TP and technology resistance. Study III.3 examines how product attributes influence perceptions of anthropomorphism, product autonomy, TP, technology resistance, and behavioral intention using data from a third survey sample. Table 16 provides an overview of all the studies.

Table 16: Overview of studies in Paper III

	Study III.1	Study III.2	Study III.3
Objectives	Examination of: • The direct effects of TP on behavioral intentions. • The effects of anthropomorphism and product autonomy on behavioral intention and TP. • The effects of product autonomy and anthropomorphism on TP.	• Investigation of the effects of anthropomorphism, product autonomy, and TP on technology resistance. • Replicates and extends the findings of Study III.1.	• Examination of the effects of product attributes on anthropomorphism, product autonomy, TP, technology resistance, and behavioral intention. • Replicates and extends the findings of Studies III.1 and III.2.
Sample	N = 271	N = 311	N = 450
Technologies presented	Smart speaker, smart watch, smart vacuum cleaner (allocated via lottery)	Smart vacuum cleaner (available on market)	Smart vacuum cleaner (concepts)
Research design	Quantitative survey design	Quantitative survey design	Quantitative survey design
Analysis approach	Structural equation modelling	Structural equation modelling	Structural equation modelling
Independent variable(s)	Anthropomorphism, product autonomy	Anthropomorphism, product autonomy	Human-like attributes, paternalistic attributes
Mediator(s)	Technology paternalism	Technology paternalism	Anthropomorphism, product autonomy, technology paternalism
Moderator(s)	N/A	Metaphoric thinking, product involvement, consumer domain-specific innovation, experience in the product category	N/A
Dependent variable(s)	Behavioral intention	Technology resistance	Behavioral intention, technology resistance

4.3.2 Study III.1: Effects of TP, product autonomy and anthropomorphism on behavioral intention

The first study examines both the direct effects of TP on behavioral intention and how perceptions of anthropomorphism and product autonomy affect adoption intention and TP. Figure 6 at the end of Section 3.2 summarizes the hypotheses and results of Study III.1.

Method

A total of 271 consumers (all participants between 18 and 65 years old, M_{age} = 43 years, SD_{age} = 13 years, 44% male; see Table 17 for details) were recruited through an online consumer research panel. In the first part of the survey, participants were introduced to one out of three smart products (randomly assigned; smart products used in this survey: smartwatch, smart speaker, smart vacuum cleaner; see Figure 16 in the appendix for the visual stimuli used). The second part consisted of several separate themes, which were randomly ordered. One part was the TP scale developed in Paper II of this dissertation (Rochi et al., 2024). The survey included quality checks (e.g., "Please select the value 'two'"). In addition, the participants were asked to rate product anthropomorphism, product autonomy, and behavioral intention to use the smart product presented. Demographic questions completed the questionnaire.

Table 17: Descriptive analysis sample (Study III.1)

Sex	%	Age in full years		Profession	%	Income (single net income per month)	%
Male	43.5	Min	18	Full-time employed	52.8	Less than 1,500 EUR	31.4
Female	56.5	Max	65	Working part-time	12.9	1,501 to 2,000 EUR	14.0
		Average	42.86	Self-employed	2.6	2,001 to 2,500 EUR	15.1
		Median	44.00	Unemployed	7.0	2,501 to 3,000 EUR	14.0
		SD	13.41	Retired/pensioned	7.0	3,001 to 3,500 EUR	5.9
				School/study	8.9	3,501 to 4,000 EUR	4.4
				In training	1.1	4,001 to 4,500 EUR	2.6
				Other (unable to work, etc.)	7.7	4,501 to 5,000 EUR	3.3
						More than 5,000 EUR	1.1

Measures, validity, and reliability

TP was measured on a 16-item three-dimensional scale adopted from Rochi et al. (2024). Product autonomy was measured on a 4-item scale (Rijsdijk & Hultink, 2003). Anthropomorphism was measured on a 3-item scale (adapted from Epley et al., 2007). Behavioral intention to use the smart product as the dependent variable was measured on a 3-item scale (adapted from Venkatesh et al., 2003). Age and gender, two common variables in technology acceptance research, and the product category (e.g., smart watch, smart vacuum cleaner) were included as control variables. Table 18 shows Cronbach's alpha, composite reliabilities (CR), and average variance extracted (AVE), as well as all single factor loadings of all latent constructs used in Study III.1. For a full list of all items used in Study III.1, please see Table 39 in the appendix.

Cronbach's alphas of all the measures vary from .71 to .91, surpassing the acceptable level of .70 (Nunnally, 1978). Composite reliability ranged from .73 to .91, which is above the minimum level of .70 suggested by Hair et al. (2019). All AVE values (except TP with .489) were above the threshold of .50, reflecting adequate convergent validity (Hair et al., 2019). Concerning the low AVE of the TP construct, Fornell and Larcker (1981) stated that if AVE is less than .50 but composite reliability is higher than .60, the convergent validity of the construct is still adequate. This holds true for TP (CR = .734). For discriminant validity, the model met the HTMT threshold of < .90 (see Table 19; Henseler et al., 2015).

Table 18: Alpha, CR, and AVE (Study III.1)

Latent construct	Factor loadings	Cronbach's alpha	CR	AVE
TP (3 dimensions)		.711	.734	.489
D1: autonomy cut (7 items; item parceling)*	.789			
D2: overruling options (5 items; item parceling)*	.778			
D3: welfare intention (4 items; item parceling)*	.488			
Behavioral intention (3 items)		.911	.914	.779
If I had a *technology* like this in my household, I would use it as often as possible.	.943			
If I had a *technology* like this in my household, I would use it very intensively.	.807			
If there was a *technology* like this in my household, I would be happy to use it.	.892			
Anthropomorphism (3 items)*		.846	.851	.658
The *technology* looks almost like a human.	.732			
The *technology* almost looks as if it has a mind of its own.	.898			
It almost seems as if the *technology* has its own intentions.	.795			
Product autonomy (4 items)		.860	.860	.607
The *technology* determines itself how it conducts tasks.	.751			
The *technology* makes decisions by itself.	.806			
The *technology* takes the initiative.	.822			
The *technology* does things by itself.	.734			

Note: CR = composite reliability; AVE = average variance extracted; all factor loadings are significant (all $p < .001$); * = the sub-dimensions of TP were estimated using item-parceling (all items of every dimension can be found in Table 39 in the appendix); average composite scores were used for sub-factors. "*The technology*" serves as a placeholder for the technology under consideration; * Anthropomorphism item 4 was deleted due to low Cronbach´s alpha value.

Table 19: HTMT ratios in SEM (Study III.1)

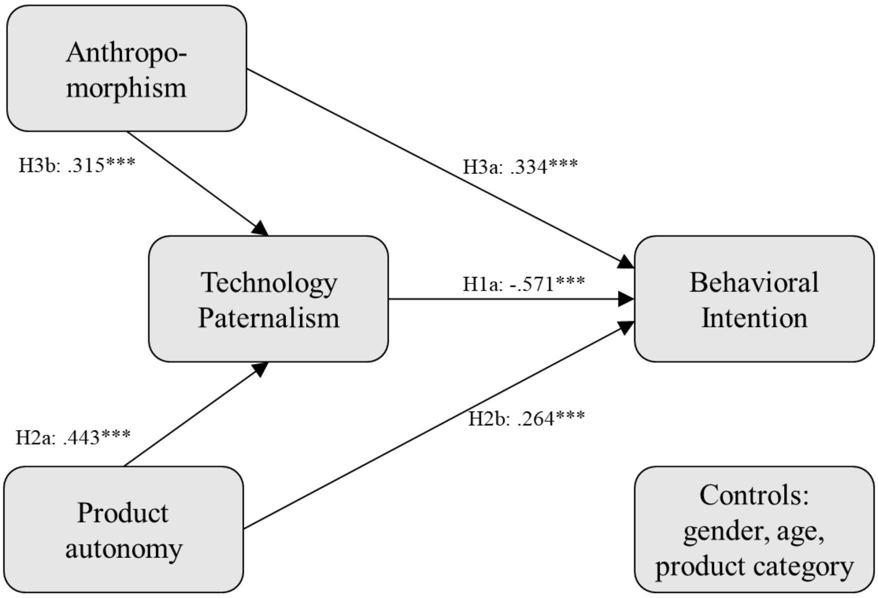
HTMT	TP	AN	BI	PA
TP				
AN	.523			
BI	−.201	.145		
PA	.541	.172	.069	

Note: Significance of correlations: * $p < .001$; AN = anthropomorphism, BI = behavioral intention, PA = product autonomy

Structural model assessment

A structural equation model generated with the software Mplus (Muthén & Muthén, 1998-2017) was used to test the proposed relationships. The fit indices for the model fell within the acceptable range: CMIN/df = 2.362 (181.907; 77), TLI = .92, CFI = .94, SRMR = .07, and RMSEA = .70 (LOW_{90} .058 /$HIGH_{90}$ .084). The squared multiple correlations (R^2) for all dependent variables can be found in Table 26. Regarding the developed hypotheses, it was found that the impact of TP on behavioral intention was negative and significant (b = –.557, t = –6.313, p < .001), supporting H1a. Furthermore, H2a and H2b were supported, as product autonomy impacted TP and behavioral intentions, both positively and at a significant level (b = .418, t = 5.669, p < .001, and b = .284, t = 3.710, p < .01, respectively). H3a and H3c were supported, as anthropomorphism impacted behavioral intention and TP positively and significantly (b = .303, t = 3.798, p < .001, and b = .343, t = 4.411, p < .001, respectively). For the control variables of age and gender, the results indicated that TP, product autonomy, and anthropomorphism were uncorrelated with both. It was found that age had a significant effect on behavioral intention (b = –.132, t = –2.122, p < .05), but not on the other constructs in the structural model. This is not surprising, as older consumers are less likely to adopt innovative products (Bae et al., 2021). Table 26 summarizes all SEM results.

Concerning hypotheses H2d and H3d, the author investigated the potential mediating effects of TP on 1) the relationship between product autonomy and behavioral intention and 2) the relationship between anthropomorphism and behavioral intention. Product autonomy predicted the mediator TP significantly (b = .418, p < .001), which in turn predicted behavioral intention significantly (b = –.557, p < .001). It was found that the indirect effect of product autonomy on behavioral intention through TP from bootstrap analysis (5,000 samples) was negative and significant (b = –.408; p < .001, CI95[–.694, –.236]. The direct effect was positive (b = .427 CI95[.171, .712]) and significant (p < .01), resulting in a competitive mediation effect. For H3d, the results showed similar patterns. Anthropomorphism predicted the mediator TP significantly (b = .343, p < .001), which in turn predicted behavioral intention significantly (see above). The author found the total indirect effect from the bootstrap analysis to be negative and significant (b = –.302, p < .01, CI95[–.538, –.128]. The direct effect was positive (.561, p < .001, CI95[.305, .873]), resulting in a competitive mediation effect (see Table 27 for an overview of mediation analysis results). Hence, for both mediations, TP can be interpreted as a suppressor that substantially decreases the magnitude of the positive total effects of product autonomy and anthropomorphism on behavioral intention (Hair et al., 2021). Table 27 gives an overview of all mediation analyses.



H2d: product autonomy → TP → behavioral intention; competitive mediation (indirect effect b = -.408***)
H3d: anthropomorphism → TP → behavioral intention; competitive mediation (indirect effect b = -.302**)
Controls: Age → behavioral intention (b = -.132*); product category (smart watch) → behavioral intention (b = .157*)

Figure 6: Study design and hypotheses tested in Study III.1

Discussion

By utilizing data from a German online panel, the present study developed a structural equation model including both direct and mediation effects, wherein product autonomy and anthropomorphism directly affect both TP and behavioral intention. Additionally, the effects of TP on behavioral intention were modeled. In line with H1a, it was found that TP negatively affected behavioral intention. This is in line with the theoretical considerations made by Rochi (2023), and it represents the first empirical evidence of a negative effect of TP on behavioral intention. The findings support Hypothesis H2a, which posited that product autonomy significantly affects TP. These findings are congruent with other related research outcomes, such as the study by Lucia-Palacios and Pérez-López (2021), which showed that high levels of product autonomy can lead to increased product intrusiveness and reduced usefulness.

Hypothesis H2b was also supported, and higher product autonomy was found to be related to higher behavioral intention. This is in line with related work that found higher product autonomy to be positively related to usage intention (G. Li et al., 2015). This study also showed that anthropomorphism positively affected both behavioral intention and TP. The present study's findings are consistent with earlier research findings demonstrating that anthropomorphism positively influences behavioral intention (Waytz et al., 2014; L. Zhang et al., 2021), and Hypotheses H3a and H3b were supported.

To delve deeper, this study examined the mediation effects of TP on the relationships between anthropomorphism and behavioral intention and between product autonomy and behavioral intention. The findings revealed a significant mediation effect in both cases and underlined the importance of TP for adoption behavior related to smart products. These mediation effects reveal that anthropomorphism and product autonomy increase both behavioral intention and TP, which, in turn, decreases behavioral intention. This illustrates that "the more support the better" does not hold anymore (Rochi, 2023). In certain cases, TP can act as a suppressor, which dampens the positive effects of increased product autonomy and anthropomorphism on behavioral intention.

4.3.3 Study III.2: Effects of TP, product autonomy, and anthropomorphism on technology resistance

One goal of Study III.2 was to replicate some of the results from Study III.1 with a new sample and to investigate the effects of anthropomorphism, product autonomy, and TP on technology resistance (H1b, H2a, H2c, H3b, and H3c). Therefore, a second study with a new sample was conducted to further investigate the above hypothesized relations between anthropomorphism, TP, product autonomy, and technology resistance. Figure 7 shows the above hypothesized relationships relevant to Study III.2.

Method

A total of 311 participants (all participants between 18 and 65 years old, M_{age} = 43 years, SD_{age} = 13 years, 45% male; for details, see Table 20) were enlisted through an online consumer research panel. In the initial segment of the survey, the author presented a commercially available smart vacuum cleaner (see visual stimuli in Figure 17 in the appendix). The second section encompassed various distinct themes presented in randomized order. One segment involved the use of the TP scale (Rochi et al., 2024), accompanied by two quality checks. Additionally, participants were prompted to assess anthropomorphism, product autonomy, and technology resistance related to the presented smart vacuum cleaner. Demographic inquiries concluded the questionnaire.

Table 20: Descriptive analysis sample (Study III.2)

Sex	%	Age in full years		Profession	%	Income (single net income per month)	%
Male	44.7	Min	22	Full-time employed	52.1	Less than 1,500 EUR	23.2
Female	55.3	Max	65	Working part-time	16.1	1,501 to 2,000 EUR	15.1
		Average	42.60	Self-employed	4.8	2,001 to 2,500 EUR	13.5
		Median	38	Unemployed	3.5	2,501 to 3,000 EUR	14.1
		SD	13.18	Retired/pensioned	11.9	3,001 to 3,500 EUR	6.1
				School/study	5.5	3,501 to 4,000 EUR	8.7
				In training	1.3	4,001 to 4,500 EUR	4.8
				Other (unable to work, etc.)	4.8	4,501 to 5,000 EUR	1.6
						More than 5,000 EUR	5.5

Note: N = 311

Measures, validity, and reliability

TP, product autonomy, and anthropomorphism were measured with the same items as in Study III.1. Technology resistance was measured with a 4-item ad hoc scale. Again, age and gender were included as control variables. Table 21 displays the Cronbach's alpha, CR, AVE, and single factor loadings of all latent constructs used in Study III.2. For a full list of all items used in Study III.2, please see Table 39 in the appendix.

The Cronbach's alpha of all the measures varied from .83 to .98, surpassing the acceptable level of .70 (Nunnally, 1978). Composite reliability ranged from .83 to .98, which meets the appropriate level of .70 suggested by Hair et al. (2019). All AVE values were above the threshold of .50, reflecting adequate convergent validity (Hair et al., 2019). For discriminant validity, the model met the HTMT threshold of < .90 (see Table 22; Henseler et al., 2015).

Table 21: Alpha, CR, and AVE (Study III.2)

Latent construct	Factor loadings	Cronbach's alpha	CR	AVE
TP (3 dimensions)		**.828**	**.844**	**.650**
D1: autonomy cut (7 items; item parceling)*	.923			
D2: overruling options (5 items; item parceling)*	.856			
D3: welfare intention (4 items; item parceling)*	.604			
Resistance (4 items)		**.976**	**.977**	**.912**
If there were such a robot vacuum cleaner in my household, I would deliberately not use it.	.932			
If there was a robot vacuum cleaner like this in my household, I'd reject it out of hand.	.958			
If there was such a robot vacuum cleaner in my household, I would refuse to use it.	.972			
If there was such a robot vacuum cleaner in my household, I would be totally "against" it.	.958			
Anthropomorphism (4 items)		**.880**	**.883**	**.655**
The *technology* looks almost like a human.	.698			
The *technology* almost looks as if it has a mind of its own.	.885			
It almost seems as if the *technology* has its own intentions.	.851			
It seems as if the *technology* is emotional in a way.	.790			
Product autonomy (4 items)		**.850**	**.851**	**.590**
The *technology* determines itself how it conducts tasks.	.696			
The *technology* makes decisions by itself.	.851			
The *technology* takes the initiative.	.816			
The *technology* does things by itself.	.697			

Note: CR = composite reliability; AVE = average variance extracted; all factor loadings are significant (all p < .001); * = the sub-dimensions of TP were estimated using item-parceling (all items of every dimension can be found in Table 39 in the appendix); average composite scores were used for sub-factors; "*The technology"* serves as a placeholder for the technology under consideration.

Table 22: HTMT ratios in SEM (Study III. 2)

HTMT				
	TP	**AN**	**RES**	**PA**
TP				
AN	.704			
RES	.387	.225		
PA	.481	.572	−.083	

Note: Significance of correlations: * p < 0.001; AN = anthropomorphism, RES = resistance, PA = product autonomy

Structural model assessment

A structural equation model generated with Mplus (Muthén & Muthén, 1998-2017) was used to test the proposed relationships. The fit indices for the model fell within the acceptable range: CMIN/df = 2.680 (284.061/106), TLI = .94, CFI = .96, SRMR = .07, and RMSEA = .07 ($RMSEA_{LOW90}$ .063/$RMSEA_{HIGH90}$ .084). The squared multiple correlations (R^2) for all dependent variables can be found in Table 26.

It was found that the impact of TP on technology resistance was positive and significant (b = .537, t = 5.725, p < .001), supporting H1b. H2c was not supported, as product autonomy impacted technology resistance negatively (b = −.330, t = −3.708, p < .001) rather than positively. Furthermore, the results did not show evidence that product autonomy affected TP ($b = .071$, $t = 0.941$, $p = .346$), and H2a was not supported.[12] Anthropomorphism did not impact technology resistance negatively and significantly ($b = .083$, $t = 0.948$, $p = .343$), so H3b was not supported, but it did affect TP positively and significantly ($b = .547$, $t = 7.065$, $p < .001$), supporting H3c. For the control variables of age and gender, the results indicated that TP and technology resistance were uncorrelated with both. Table 26 summarizes all SEM results.

To test Hypotheses H2e and H3e, the author explored the potential mediation effects of TP in 1) the association between product autonomy and technology resistance and 2) the connection between anthropomorphism and technology resistance. As product autonomy did not significantly predict the mediator TP, no significant indirect effect ($b = .038$, $p = .376$) was found, and H2e was not supported. For H3e, anthropomorphism predicted the mediator TP significantly, which in turn predicted technology resistance significantly (see above). The indirect effect from the bootstrap analysis was positive and significant (.293, $p < .001$; CI95 [.180, .450]. The direct effect was non-significant (.083; $t = 0.948$, $p = .343$), indicating a full mediation effect (see Table 27 for an overview of the mediation analysis results).

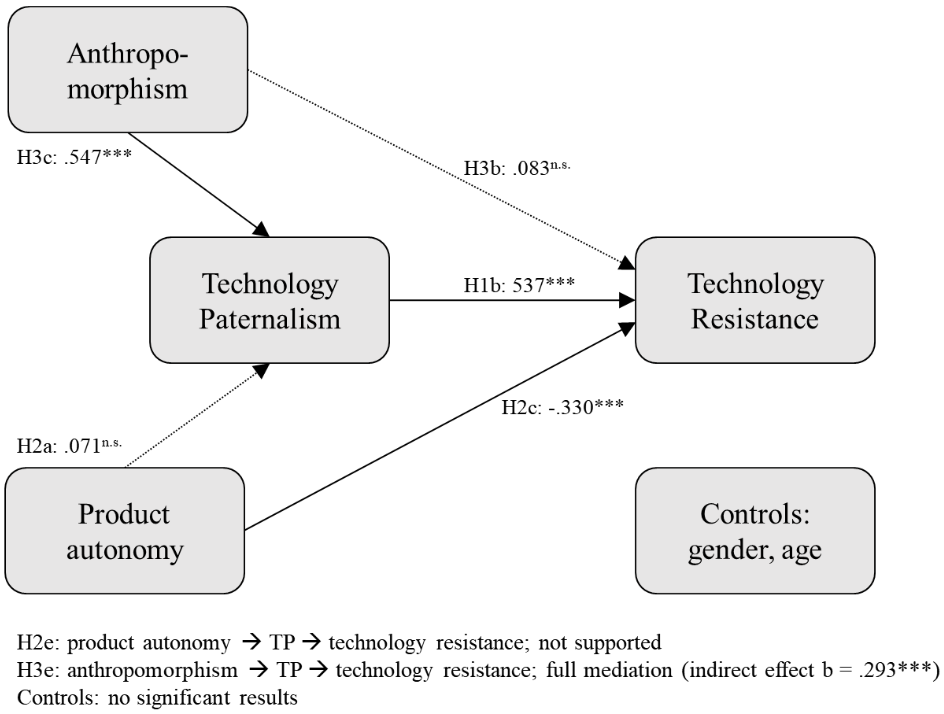


Figure 7: Study design and hypotheses tested in Study III.2 (dotted lines represent non-significant paths)

[12] At first glance, this seems to contradict the results of Study III.1. However, it should be noted that Study III.1 initially included three different product categories. When considering only the data from participants exposed to the smart vacuum cleaner, the results of Study III.1 show similar patterns. For further information, see Figure 13 to Figure 15 in the appendix.

Discussion

By utilizing a new dataset from a German online panel, Study III.2 partly validated the results from Study III.1 by building a structural equation model that included both direct and mediation effects, wherein product autonomy and anthropomorphism directly affected both TP and technology resistance. The results support the assertion that TP positively affects technology resistance to the presented smart vacuum cleaner (H1b). This is in line with Rochi's (2023) theoretical considerations and represents the first empirical evidence of the effect of TP on technology resistance. Further, this study replicated the results of Study III.1, as anthropomorphism directly affected TP (H3c).

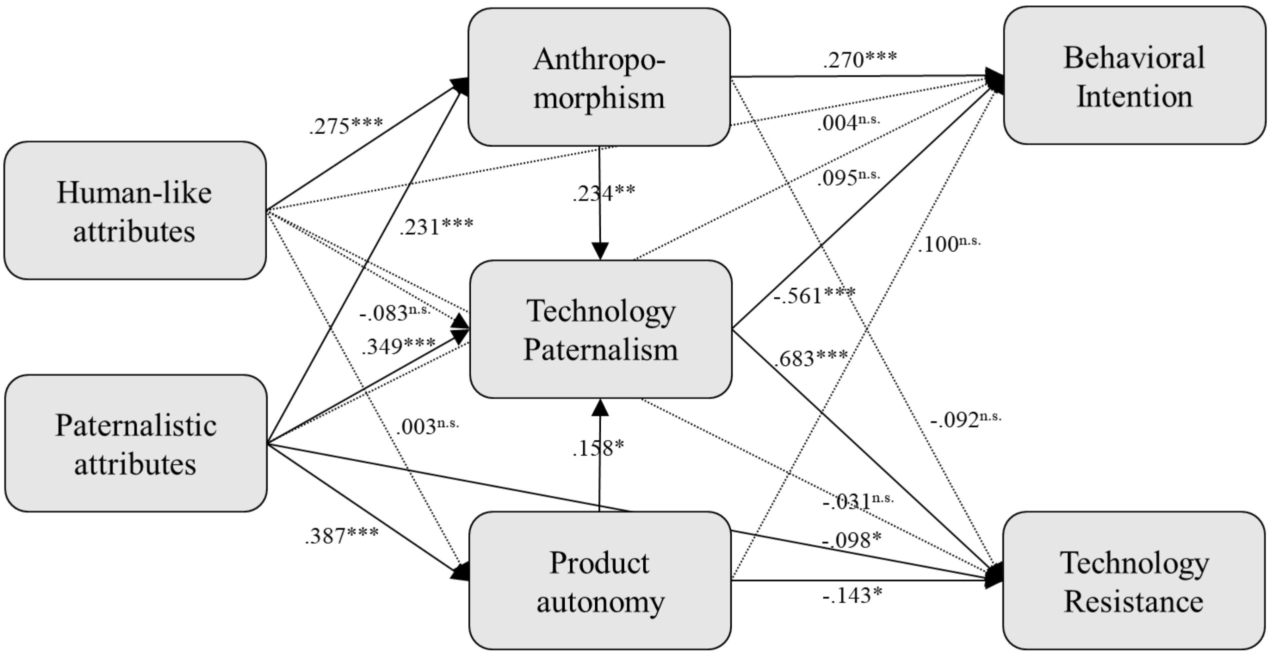
No significant effect was found for the effect of anthropomorphism on technology resistance (H3b). It might be expected that because anthropomorphism significantly and positively affected behavioral intention in Study III:1, the same construct should negatively affect technology resistance. This was not the case, underlining that resistance and acceptance cannot be interpreted as directly opposed constructs (see Section 2.2. for further details).

In contrast to Study III.1, in this set-up, no significant evidence was found that product autonomy affects TP (H2a) or technology resistance (H2c). These non-significant effects were both replicated in Study III.1 when only including data from participants who were presented with a smart vacuum cleaner. This underlines the assumption that many resistance-related inhibitors are specific to particular product categories (e.g., Bhattacherjee & Hikmet, 2007; Craig et al., 2019). Interestingly, the effect of product autonomy on technology resistance was negatively significant, which is in contrast to the hypothesized relationship.

To delve deeper into the significance of TP, the study examined the mediation effects of TP on the relationships between anthropomorphism and technology resistance (H3e) and between product autonomy and technology resistance (H2e). The findings revealed a significant full mediation effect of TP in the relationship between anthropomorphism and technology resistance. However, there was no empirical evidence of TP mediating the relationship between product autonomy and technology resistance.

4.3.4 Study III.3: Effects of paternalistic and human-like attributes

After investigating the effect of TP on technology resistance and behavioral intention in Studies III.1 and III.2, the author examined how product attributes influence the perception of anthropomorphism, product autonomy, TP, technology resistance, and behavioral intention with data from a third survey sample. To do so, the effects on behavioral intention and technology resistance were not tested separately (as in Studies III.1 and III.2), but both were included as dependent variables in the structural equation model. Figure 8 provides an overview of the tested relationships. It was expected that more human-like attributes would have an impact on the perception of anthropomorphism, and that more paternalistic attributes would increase TP, subsequently affecting both behavioral intention and technology resistance.



H2e: competitive mediation product autonomy → TP → technology resistance
H3e: competitive mediation anthropomorphism → TP → technology resistance
Controls: Age → behavioral intention (b = -.095*); Gender → technology resistance (b = .108**)
Note: standardized Pearson correlations (2-tailed); *p < 0.05; **p < 0.01; ***p < 0.001; n.s. = not significant; Estimator = ML; Bootstrapping = 5000 re-samples

Figure 8: Study design and hypotheses tested in Study III.3 (dotted lines represent non-significant paths)

Method

In Study III.3, the author deliberately manipulated both TP and anthropomorphism. Past research was followed in conducting a pre-test with a separate sample from the same population. The paternalistic product attributes were manipulated in line with the dimensions of the definition of TP (Rochi (2023); autonomy cuts, overruling prospects, and welfare intentions). For example, paternalistic treatment conditions presented the smart vacuum cleaner with attributes as follows: “For maximum performance, [vacuum cleaner name; dependent on anthropomorphism manipulation] makes decisions independently and without informing you” (autonomy cut) or “You can make minor changes via the [vacuum cleaner name] app. [Vacuum cleaner name] functions are automated and pre-set so that it can always deliver full performance” (autonomy cut and overruling prospects), and “[vacuum cleaner name] reports its performance data to you every day and independently gives you tips on floor cleaning and general cleanliness in the household. And that’s in addition to the hours of housework it does for you!” (welfare intention). The high anthropomorphic product manipulation consisted of the product being framed as female (“JESSI,” a common German female nickname) vs. a simple product name in the low anthropomorphism condition (“IES23i”). Furthermore, in the high anthropomorphism condition, the product was visualized with more human attributes than in the low anthropomorphism condition (e.g., human-like facial attributes like “eyes”). The visual stimuli can be found in the appendix (Figure 18).

In the pre-test, the author followed the above-mentioned manipulation of anthropomorphic and paternalistic product attributes in a between-participants design. For the pre-test, 191 German participants were recruited (M_{age} = 39.7 years, 49.2% female) from a consumer research panel. The manipulation check procedure was based on previous studies in a similar context (e.g., J. Huang et al., 2024). Participants were randomly assigned to one of the four treatment conditions that served as manipulations of TP and anthropomorphism (high TP/high anthropomorphism, high TP/low anthropomorphism; low TP/high anthropomorphism; low TP/low anthropomorphism). For the TP manipulation check, participants were asked to complete the TP scale (drawn from Rochi et al., 2024; all three dimensions with $\alpha \geq .87$). The results showed that the manipulation worked as intended (t-test; $M_{TPhigh} = 3.88$ (N = 98), $M_{TPlow} = 2.31$ (N = 93), $\Delta M = 1.57$ (CI95[1.25, 1.90]), $t(189) = 9.637$, $p < .001$, $d = 1.40$). For the manipulation check of anthropomorphism, the participants completed four questions regarding product anthropomorphism (four items based on Epley et al., 2007; $\alpha \geq .88$). The results showed that the manipulation worked as intended (t-test; $M_{ANTHROhigh} = 3.42$ (N = 95), $M_{ANTHROlow} = 2.84$ (N = 96), $\Delta M = .58$ (CI95[.14, 1.02]), $t(189) = 2.600$, $p < .01$, $d = .38$).

For the main study, Study III.3, 450 consumers (all participants between 18 and 65 years old, M_{age} = 43 years, SD_{age} = 12 years, 47% male; for details, see Table 23) were recruited through a consumer research online panel. In the first part of the survey, participants were randomly assigned to one of the four treatment conditions (analogous to the pre-test). The second part contained several separate themes, which were lined up at random (TP scale by Rochi et al. (2024), anthropomorphism, product autonomy, and behavioral intention). Demographic questions completed the questionnaire.

Table 23: Descriptive analysis sample (Study III.3)

Sex	%	Age in full years		Profession	%	Income* (single net income per month)	%
Male	47.1	Min	18	Full-time employed	53.8	less than 1,500 EUR	24.0
female	52.9	Max	65	Working part-time	19.6	1,501 to 2,000 EUR	14.9
		Average	43.19	Self-employed	5.6	2,001 to 2,500 EUR	16.7
		Median	42.00	Unemployed	3.6	2,501 to 3,000 EUR	10.7
		SD	12.49	Retired/pensioned	8.7	3,001 to 3,500 EUR	10.7
				School/Study	3.8	3,501 to 4,000 EUR	4.9
				in training	0.9	4,001 to 4,500 EUR	2.4
				Other (unable to work, etc.)	4.2	4,501 to 5,000 EUR	2.4
						more than 5,000 EUR	3.1

Note: N = 450; *some participants opted not to provide responses to this question

Measures, validity, and reliability

At the beginning of the questionnaire, the participants were given detailed information about the conceptual product to be presented and further procedures (e.g., “A next-generation smart vacuum cleaner is presented below. This vacuum cleaner is currently under development. Thanks to our cooperation with the manufacturer, we have already been able to gain access to the first concept drawings and analyze them […]”). After this, the participants were presented with the manipulated product portrayal. They completed questions regarding perceived anthropomorphism and TP, behavioral intention, and technology resistance. For all measures, the Cronbach’s alpha, CR, AVE, and HTMT values surpassed acceptable levels (see Table 24 and Table 25). A list of all items used in this study can be found in Table 39 in the appendix.

Table 24: Alpha, factor loadings, CR, and AVE (Study III.3)

Latent construct	Factor loadings	Cronbach's alpha	CR	AVE
TP (3 dimensions)		.804	.815	.608
D1: autonomy cut (7 items; item parceling)*	.928			
D2: overruling options (5 items; item parceling)*	.833			
D3: welfare intention (4 items; item parceling)*	.518			
Resistance (4 items)		.973	.974	.902
If there were such a robot vacuum cleaner in my household, I would deliberately not use it.	.925			
If there was a robot vacuum cleaner like this in my household, I'd reject it out of hand.	.961			
If there was such a robot vacuum cleaner in my household, I would refuse to use it.	.970			
If there was such a robot vacuum cleaner in my household, I would be totally "against" it.	.942			
Behavioral intention (3 items)		.967	.968	.910
If I had a *technology* like this in my household, I would use it as often as possible	.973			
If I had a *technology* like this in my household, I would use it very intensively.	.950			
If there was a technology like this in my household, I would be happy to use it.	.938			
Anthropomorphism (4 items)		.837	.840	.575
The *technology* looks almost like a human.	.551			
The *technology* almost looks as if it has a mind of its own.	.867			
It almost seems as if the *technology* has its own intentions.	.839			
It seems as if the *technology* is emotional in a way.	.744			
Product autonomy (4 items)		.905	.905	.705
The *technology* determines itself how it conducts tasks.	.788			
The *technology* makes decisions by itself.	.845			
The *technology* takes the initiative.	.906			
The *technology* does things by itself.	.816			

Note: CR = composite reliability; AVE = average variance extracted; all factor loadings are significant (all p < 0.001); * = the sub-dimensions of TP were estimated using item-parceling (all items of every dimension can be found in Table 39 in the appendix); average composite scores were used for sub-factors; "*The technology*" serves as a placeholder for the technology under consideration.

Table 25: HTMT ratios in SEM (Study III.3)

HTMT	**TP**	**AN**	**RES**	**BI**	**PA**
TP					
AN	.426				
RES	.455	.032			
BI	−.266	.171	−.776		
PA	.475	.422	.054	.036	

Significance of correlations: * p < .001; AN = anthropomorphism, RES = resistance, BI = behavioral intention, PA = product autonomy

Structural model assessment

In line with the pre-test, manipulation tests showed that the manipulation worked as intended (TP manipulation: t-test; $M_{TPhigh} = 3.49$ (N = 227), $M_{TPlow} = 2.22$ (N = 223), $\Delta M = 1.27$ (CI95[1.04, 1.50]), $t(434) = 10.989$, $p < .001$ (one-sided), $d = 1.03$; anthropomorphism manipulation: t-test; $M_{ANTHROhigh} = 3.54$ (N = 230), $M_{ANTHROlow} = 2.57$ (N = 220), $\Delta M = .97$ (CI95[.69, 1.24]), $t(448) = 6.855$, $p < .001$ (one-sided), $d = .65$).

A structural equation model generated with Mplus (Muthén & Muthén, 1998-2017) was used to test the proposed relationships. The fit indices for the model fell within the acceptable range: CMIN/df = 3.058, TLI = .94, CFI = .95, SRMR = .07, and RMSEA = .07 ($RMSEA_{LOW90}$ .061/$RMSEA_{HIGH90}$ .074). The squared multiple correlations (R^2) for all dependent variables can be found in Table 26. As expected, stronger anthropomorphic attributes had a significant direct effect on the perception of anthropomorphism (b = .275;

$p < .001$). However, no support was found for the prediction that stronger human-like attributes affect behavioral intention, TP, technology resistance, or product autonomy (see Table 26 for details). Stronger manifestations of paternalistic attributes affected TP ($b = .349$; $p < .001$), technology resistance (although in a negligible way; $b = -.098$; $p <.05$), anthropomorphism ($b = .231$; $p < .001$), and product autonomy ($b = .387$; $p < .001$). There was no significant direct effect of paternalistic attributes on behavioral intention.

To further validate the results of Studies III.1 and III.2, the author again evaluated the above-motivated hypotheses. The results supported H1a/b, H2a, H2c, H3a, and H3c (for details, see Table 26). With regard to H2b (the effect of product autonomy on behavioral intention) and H3b (the effect of anthropomorphism on technology resistance), no significant effects were found in Study III.3. In Study III.3, inconsistent results were found for the mediating effects of TP in the influence of product autonomy on behavioral intention and product autonomy on technology resistance. Regarding the mediation effects, the results of Study III.3 validate Hypotheses H3d and H3e. Consistent results confirmed the competitive mediation effects of TP in the influence of anthropomorphism on both behavioral intention and technology resistance. The mediating effects of TP in the relationship between product autonomy and technology resistance, which were not significant in Study III.2, were shown to be a competitive mediation in Study III.3 (detailed results in Table 27).

To investigate the effects of human-like and paternalistic attributes on behavioral intention and technology resistance, the author conducted further mediation analyses. Paternalistic attributes had an indirect effect on behavioral intention, but there were no significant direct effects. Paternalistic attributes had both direct and indirect effects on technology resistance, resulting in competitive mediation. Anthropomorphic product attributes showed neither a direct nor indirect significant effect on behavioral intention or technology resistance (see Table 28).

Table 26: Overview of direct effects and hypotheses (Studies III.1 – III.3)

Hypothesized relationships	Standardized Estimates (t)				R² (t)			
	Study III.1	Study III.2	Study III.3	Conclusion		Study III.1	Study III:2	Study III.3
H1a: Technology paternalism → Behavioral intention (−)	−.557 (−6.313)***		−.561 (−9.248)***	Supported	BI	.246 (3.697)***		.257 (5.094)***
H1b: Technology paternalism → Technology resistance (+)		.537 (5.725)***	.683 (13.496)***	Supported	TR		.278 (4.014)***	.359 (6.982)***
H2a: Product autonomy → Technology paternalism (+)	.418 (5.669)***	.071 (0.941)$^{n.s.}$	.158 (2.502)*	Partly supported	TP	.350 (4.369)***	.367 (4.750)***	.310 (6.368)***
H2b: Product autonomy → Behavioral intention (+)	.284 (3.710)***		.100 (1.611)$^{n.s.}$	Partly supported	AN			.141 (4.005)***
H2c: Product autonomy → Technology resistance (+)		−.330 (−3.708)***	−.143 (−2.520)*	Not supported	PA			.163 (4.629)***
H3a: Anthropomorphism → Behavioral intention (+)	.303 (3.798)***		.270 (3.999)***	Supported				
H3b: Anthropomorphism → Technology resistance (−)		.083 (0.948)$^{n.s.}$	−.092 (−1.535)$^{n.s.}$	Not supported				
H3c: Anthropomorphism → Technology paternalism (+)	.343 (4.411)***	.547 (7.065)***	.234 (3.404)**	Supported				
HL−attrb. → Anthropomorphism			.275 (5.368)***					
HL−attrb. → Technology paternalism			−.083 (−1.799)$^{n.s.}$					
HL−attrb. → Product autonomy			.003 (0.069)$^{n.s.}$					
HL−attrb. → Behavioral intention			.004 (0.089)$^{n.s.}$					
HL−attrb. → Technology resistance			−.031 (−0.725)$^{n.s.}$					
Pat.−attrb. → Anthropomorphism			.231 (4.839)***					
Pat.−attrb. → Technology paternalism			.349 (7.525)***					
Pat.−attrb. → Product autonomy			.387 (8.781)***					
Pat.−attrb. → Behavioral intention			.095 (1.828)$^{n.s.}$					
Pat.−attrb. → Technology resistance			−.098 (−2.108)*					
Controls								
Age → Technology paternalism	.049 (0.786)$^{n.s.}$	−.086 (−1.595)$^{n.s.}$	−.008 (−.189)$^{n.s.}$					
Age → Behavioral intention	−.132 (−2.122)*		−.095 (−2.158)*					
Gender → Technology paternalism	−.069 (−1.149)$^{n.s.}$	.058 (1.108)$^{n.s.}$	−.050 (−1.131)$^{n.s.}$					
Gender → Behavioral intention	.062 (0.984)$^{n.s.}$		−.071 (−1.620)$^{n.s.}$					
Age → Technology resistance		.052 (1.026)$^{n.s.}$	.057 (1.346)$^{n.s.}$					
Gender → Technology resistance		−.046 (−0.904)$^{n.s.}$	.108 (2.688)**					

Note: **standardized** Pearson correlations (2-tailed); *$p < .05$; **$p < .01$; ***$p < .001$; n.s. = not significant; Estimator = ML; Bootstrapping = 5000 re-samples

Table 27: Overview of mediation effects and hypotheses (Studies III.1 – III.3)

Mediation Analysis	Unstandardized Estimates								
	Study III.1			Study III.2			Study III.3		
Relationships	**Dir. Effect (t) [CI95]**	**Indir. Effect (t) [CI95]**	**Tot. Effect (t) [CI95]**	**Dir. Effect (t) [CI95]**	**Indir. Effect (t) [CI95]**	**Tot. Effect (t) [CI95]**	**Dir. Effect (t) [CI95]**	**Indir. Effect (t) [CI95]**	**Tot. Effect (t) [CI95]**
H2d: Product autonomy → TP → Behavioral intention	.427 (3.086)** [.171, .712]	−.408 (−3.663)*** [−.694, −.236]	.019 (0.144)$^{n.s.}$ [−.245, .268]				.165 (1.575)$^{n.s.}$ [−.041, .371]	−.145 (−2.280)* [−.286, −.035]	.020 (0.177)$^{n.s.}$ [−.196, .235]
H3d: Anthropomorphism → TP → Behavioral intention	.561 (3.912)*** [.305, .873]	−.302 (−2.943)** [−.538, −.128]	.259 (2.012)* [.027, .527]				.532 (3.893)*** [.274, .812]	−.258 (−2.937)** [−.447, −.107]	.274 (2.088)* [.011, .532]
H2e: Product autonomy → TP → Technology resistance				−.330 (−3.708)*** [−.499, −.148]	.038 (0.902)$^{n.s.}$ [−.038, .130]	−.291 (−3.253)** [−.466, −.113]	−.237 (−2.445)* [−.433, −.053]	.179 (2.295)* [.042, .348]	−.058 (−0.551)$^{n.s}$ [−.272, .142]
H3e: Anthropomorphism → TP → Technology resistance				.083 (0.948)$^{n.s.}$ [−.080, .262]	.293 (4.253)*** [.180, .450]	.376 (4.289)*** [.207, .552]	−.183 (−1.519)$^{n.s.}$ [−.418, .046]	.317 (3.071)** [.127, .529]	.134 (0.994)$^{n.s.}$ [−.124, .399]

Note: **unstandardized**; *p < .05; **p < .01; ***p < .001; n.s. = not significant; Estimator = ML; Bootstrapping = 5000 re-samples;

Table 28: Mediation analysis results (Study III.3)

Relationships	Direct Effect (t) [CI95]	Indirect Effect (t) [CI95]	Total Indirect (t) [CI95]	Total Effect (t) [CI95]
Group TP → TP → BI	.362 (1.892)n.s [−.024, .761]	−.746 (−5.901)*** [−1.026, −.525]	−.606 (−4.029)*** [−.924, −.327]	−.244 (−1.380)n.s [−.591, .105]
Group TP → ANTHRO → BI		.238 (3.034)** [.113, .425]		
Group TP → PA → BI		.148 (1.527)n.s [−.029, .348]		
Group TP → ANTHRO → TP → BI		−.116 (−2.619)** [−.224, −.048]		
Group TP → PA → TP → BI		−.130 (−2.252)* [−.262, −.033]		
Group TP → TP → RES	−.376 (−2.098)* [−.745, −.040]	.916 (6.528)*** [.671, 1.228]	.924 (5.925)*** [.646, 1.266]	.547 (3.096)** [.197, .882]
Group TP → ANTHRO → RES		−.082 (−1.436)n.s [−.210, .015]		
Group TP → PA → RES		−.212 (−2.309)* [−.414, −.049]		
Group TP → ANTHRO → TP → RES		.142 (2.655)** [.060, .271]		
Group TP → PA → TP → RES		.160 (2.268)* [.041, .322]		
Group Anthro → TP → BI	.015 (0.089)n.s. [−.322, .350]	.178 (1.783)n.s. [−.007, .386]	.324 (2.726)** [.110, .577]	.340 (1.895)n.s. [−.018, .577]
Group Anthro → ANTHRO → BI		.283 (3.095)** [.137, .508]		
Group Anthro → PA → BI		.001 (0.058)n.s. [−.041, .047]		
Group Anthro → ANTHRO → TP → BI		−.138 (−2.667)** [−.272, −.059]		
Group Anthro → PA → TP → BI		−.001 (−0.064)n.s. [−.035, .034]		
Group Anthro → TP → RES	−.188 (−0.725)n.s. [−.449, .198]	−.219 (−1.800)n.s. [−.472, .008]	−.148 (−1.173)n.s. [−.408, .089]	−.266 (−1.481)n.s. [−.623, .072]
Group Anthro → ANTHRO → RES		−.097 (−1.433)n.s. [−.249, .020]		
Group Anthro → PA → RES		−.002 (−0.064)n.s. [−.057, .054]		
Group Anthro → ANTHRO → TP → RES		.169 (2.745)** [.070, .319]		
Group Anthro → PA → TP → RES		.001 (0.064)n.s. [−.042, .042]		

Note: **unstandardized**; *p < .05; **p < .01; ***p < .001; n.s. = not significant; Estimator = ML; Bootstrapping = 5000 re-samples; BI = behavioral intention; RES = technology resistance; ANTHRO = anthropomorphism; PA = product autonomy

Discussion

This study replicated the previously established effects of TP on both technology resistance and behavioral intention. By utilizing a new dataset from a German online panel, Study III.3 validated the effects found in Studies III.1 and III.2 by building an SEM with direct and indirect effects. No empirical evidence was found that product autonomy directly affected behavioral intention in this study. Furthermore, anthropomorphism had no effect on technology resistance, which is the same result found in Study III.2. Concerning the mediation effects of TP on the relationships between product autonomy and technology resistance/behavioral intention (H2e/H3e), and anthropomorphism and technology resistance/behavioral intention (H3e/H3d), the findings did not fully validate all results from Studies III.1 and III.2. The results of Study III.3 indicate that product autonomy affected behavioral intention only indirectly through TP (no significant direct effect). On the effect of technology resistance, there was (again) a competitive mediation effect, with product autonomy directly affecting technology resistance negatively and indirectly affecting technology resistance positively through TP. The same was true for anthropomorphism, which directly affected behavioral intention positively but indirectly affected behavioral intention negatively through TP. This study did not find any direct significant effect of anthropomorphism on technology resistance, but there was a mediation effect of anthropomorphism on technology resistance through TP, resulting in a full mediation effect.

4.3.5 Exploratory moderation analysis for Study III.2

Rochi (2023) proposed that the anthropomorphic design of smart products may also serve as a moderator affecting the intensity of the relationship between TP and technology resistance and adoption. The author tested this proposition (as well as the hypothesis that anthropomorphism acts as an antecedent of TP and a mediator). Rochi (2023) also proposed that the effect identified in H1b (the effect of TP on technology resistance) may not be equal for all consumers. To better understand whether and how this effect is impacted by other variables, several exploratory moderation analyses were conducted. As user attributes can be strong moderators, such as computer self-efficacy (Brusso, 2015), trust (Chin et al., 2024), or consumers' privacy concerns and willingness to self-disclose (Song et al., 2021), the author focused on personal attributes as moderators. In the context of smart product adoption, he identified specific user attributes (specifically, former product experience (a moderator proposed by Rochi, 2023), metaphoric thinking, product involvement, and consumer domain-specific innovation) as potential moderating variables influencing the connection between TP and technology resistance. All items used for the moderation analyses can be found in Table 39 in the appendix.

Anthropomorphism as potential moderator

Products featuring likable characteristics, such as friendly eyebrow movements, are generally more persuasive and face less psychological resistance (Ghazali et al., 2018a). Additionally, when intelligent devices use aggressive language, it tends to provoke stronger psychological opposition (Roubroeks et al., 2010). Traits like a human-like appearance (Waytz et al., 2014; Złotowski et al., 2015) and social-emotional capabilities (Wirtz et al., 2018) are known to enhance the acceptance of intelligent products. However, anthropomorphism can also negatively impact user acceptance (Gursoy et al., 2019; Lin et al., 2020; L. Lu et al., 2019), can trigger adverse emotional reactions (R. Fu & Xu, 2021), and may lead to detrimental effects (Sætra, 2020). Hence, the more human-like the attributes, the more intense the emotional reactions, both positive and negative (Chandler & Schwarz, 2010; R. Fu & Xu, 2021), making perceptual TP more probable for anthropomorphic products.

Product category experience as potential moderator

Rochi (2023) proposed in his conceptual article that product experience may moderate the effects of TP on behavioral intention and resistance, as previous experience often contributes to a perception of ease of use (Venkatesh, 2000). Consumers who have used similar technologies in the past may perceive innovations as less complex, which positively influences their acceptance (Venkatesh, 2000). Furthermore, consumers' prior experience and familiarity with technology significantly influences their adoption of new innovations (Saaksjarvi, 2003), and consumers experienced in interactions with innovative technologies perceive lower risks as they have successfully navigated similar situations in the past (Ziamou, 2002).

Metaphoric thinking as potential moderator

The use of metaphors increases our powers of perception about the world around us and our understanding of it (Jaynes, 1976). For example, it can be very difficult to comprehend the meaning of intangible concepts (like TP) without understanding them as something more directly perceived (e.g., a color or a taste; (Lakoff & Johnson, 1980, 1999). Therefore, conceptual metaphors exert an influence on both cognitive processing and behavior (Landau et al., 2010). Past research provides examples of this phenomenon, such as individuals perceiving others as friendlier when holding a warm cup (versus a cold one), consistent with metaphors linking social warmth and physical warmth (Williams & Bargh, 2008). Applied to the perception of smart products, individuals with a strong ability to think metaphorically may be better able to understand paternalistic qualities or characteristics. Therefore, the ability to engage in metaphorical thinking can play a moderating role in shaping the extent to which products are perceived as paternalistic.

Product involvement as potential moderator

Consumer product involvement, defined as the perceived personal importance of acquiring, consuming, and disposing of a product, shapes decision-making behaviors (Celsi & Olson, 1988). Varying involvement levels lead to different decision-making and information-search behaviors (Laurent & Kapferer, 1985). Product involvement can influence behavior in adopting innovations (Foxall & Bhate, 1991, 1993). H.-C. Wang et al. (2006) confirmed the moderating role of consumer involvement in adoption-related settings (such as brand loyalty, perceived risk, and attitudinal loyalty).

Consumer domain-specific innovation as potential moderator

Consumer domain-specific innovativeness is understood as the trend in consumers' understanding and adoption of innovation (or a new product) in a specific field, which can be used to measure the degree of consumer innovativeness (Goldsmith & Hofacker, 1991; Kaushik & Rahman, 2014). It can play a significant role in moderating direct effects in technology acceptance and resistance research, as highly innovative consumers are more likely to adopt new technologies than those with lower levels of innovativeness (Leicht et al., 2018).

Results: Exploratory moderation analysis Study III.2

We calculated the moderation analysis in Mplus (Muthén & Muthén, 1998-2017), yielding unstandardized coefficients. Bootstrapping with 5000 re-samples was employed to compute the confidence intervals. The author centered the continuous variables to prevent multicollinearity issues (Cohen et al., 2003).

The interaction between TPS and anthropomorphism was significant (ΔR^2 = 16.4%, b = .200, SE = .051, t = 3.948, $p < .001$, CI95[.101, .300]), indicating that the relationship between TP and technology resistance was moderated by anthropomorphism. With a higher perception of anthropomorphism, the effect of TP on technology resistance became stronger. See Figure 9 for a graphical representation.

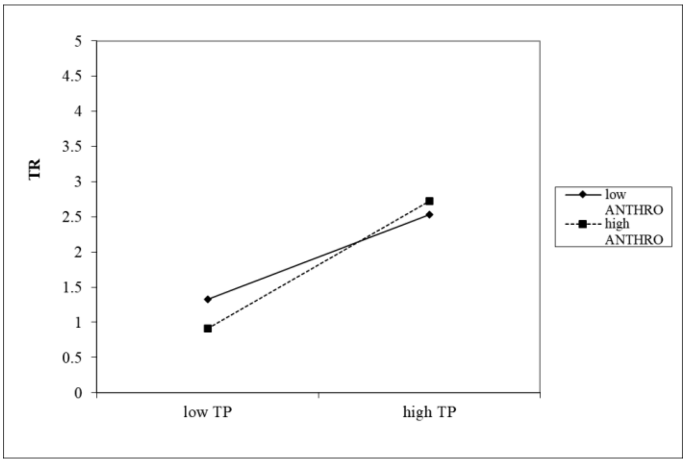


Figure 9: Moderation effect of TP x anthropomorphism; ANTHRO = anthropomorphism; TR = technology resistance

To test the interaction between TP and experience with a smart vacuum cleaner, the actual ownership of such a smart device was used as a proxy variable. The interaction between TPS and ownership (ownership = 1; no ownership = 0) was significant ($\Delta R^2 = 16.9\%$, b = .446, SE = .160, t = 2.796, p < .01, CI95[.133, .759]), indicating that the relationship between TP and technology resistance was moderated by experience with smart vacuum cleaners. See Figure 10 for a graphical representation.

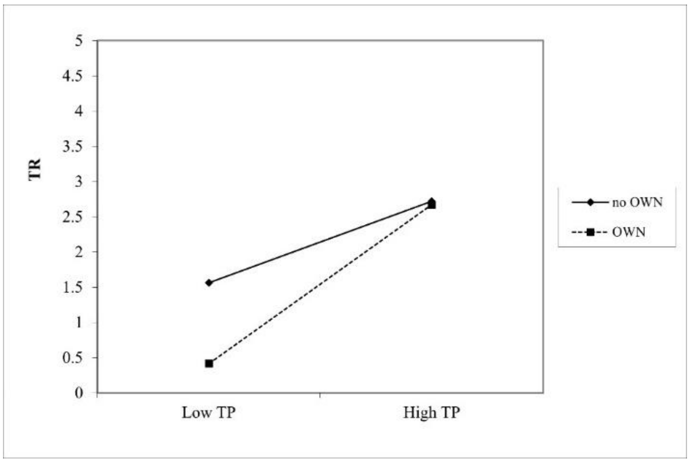


Figure 10: Moderation effect of TP x ownership; OWN = ownership; TR = technology resistance

Furthermore, the moderation analysis did not support the prediction that metaphoric thinking moderates the effect of TP on technology resistance (b = −.056, SE = .124, t = −0.454, p = .650). On the other hand, product involvement significantly moderated the relationship between TP and technology resistance ($\Delta R^2 = 34.9\%$, b = .161, SE = .050, t = 3.249, p < .01, CI95[.064, .258]). See Figure 11 for a graphical representation.

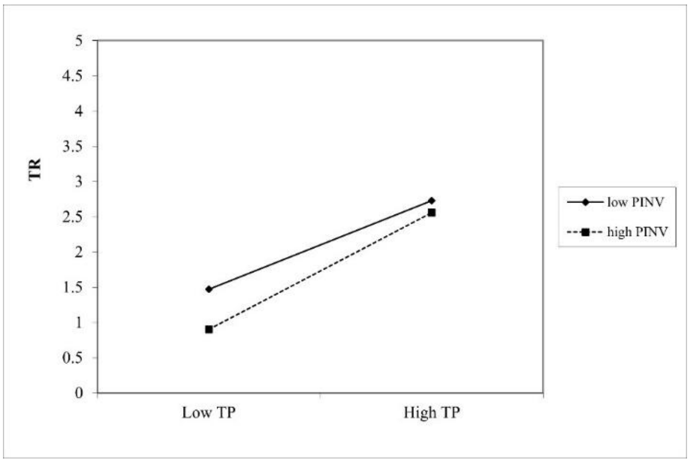


Figure 11: Moderation effect of TP x Product involvement; PINV = product involvement; TR = technology resistance

The interaction between TPS and innovativeness was significant (ΔR^2 = 17.6%, b = .158, SE = .051, t = 3.084, p < .01, CI95[.057, .258]), indicating that the relationship between TPS and behavioral intention was moderated by innovativeness. See Figure 12 for a graphical representation. All results of the moderation analysis can be found in Table 29.

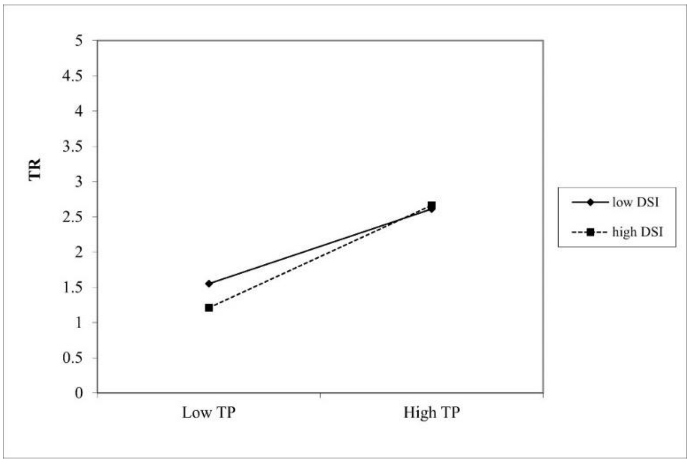


Figure 12: Moderation effect of TP x Domain-specific innovativeness; DSI = domain-specific innovativeness; TR = technology resistance

Table 29: Moderation analysis results (Study III.2)

Relationship	Coeff.	SE	t-value	p-value
ANTHRO → TR	−.112	.080	−1.401	n.s.
TP*ANTHRO → TR	.200	.051	3.948	***
Ownership → TR	−.597	.166	−3.596	***
TP*Ownership → TR	.446	.160	2.796	**
TP → TR	482	.085	5.655	***
META → TR	.084	.130	0.651	n.s.
TP*META → TR	−.056	.124	−0.545	n.s.
PINV → TR	−.371	.053	−6.991	***
TP*PINV → TR	.161	.050	3.249	**
DSI → TR	−.145	.063	−2.315	*
TP*DSI → TR	.158	.051	3.084	**

Note: **Unstandardized**; *p < .05; **p < .01; ***p < .001; n.s. = not significant; Estimator = ML; Bootstrapping = 5000 re-samples; SE = Standard Error; ANTHRO = anthropomorphism; TR = technology resistance; META = metaphoric thinking; PINV = product involvement; DSI = domain specific innovativeness

Discussion

The results of the exploratory moderation analysis provided valuable insights into the effects of moderator variables on the relationship between technology resistance and TP. The interaction between TP and anthropomorphism significantly affected technology resistance. With higher perception of anthropomorphism, the positive effect of TP on technology resistance was stronger. This is in line with research by Chandler and Schwarz (2010) and R. Fu and Xu (2021) who showed that human-like product attributes can mount the intensity of emotional responses. Second, using ownership of a smart vacuum cleaner as a proxy for experience, the analysis found a significant interaction between TP and ownership. This suggests that those who have experience with smart vacuum cleaners are more likely to develop technology resistance. This is contrary to the assumptions that consumers with product experience show higher acceptance (Venkatesh, 2000), and that users with experience with innovative product interactions perceive lower risks (Ziamou, 2002). One reason for this could be that the presented concepts show stronger autonomous and TP-enforcing features, as the (former) smart vacuum cleaner owners are used to. This would mean a disturbance of their psychological equilibrium (Heider, 1958; Talke & Heidenreich, 2014), which makes them choose to resist instead of adapting to a new situation (Talke & Heidenreich, 2014). Furthermore, no evidence was found that the influence of TP on technology resistance was moderated by individuals' metaphoric-cognitive processes. Fourth, the interaction between TP and product involvement significantly predicted technology resistance. This implies that individuals with high involvement are more likely to exhibit increased technology resistance. This is consistent with research by H.-C. Wang et al. (2006), who showed that involvement plays an important role in the perception of adoption-relevant constructs, such as perceived risk, and attitudinal loyalty. Similarly, the interaction between TP and innovativeness was significant, indicating that those with higher levels of innovativeness are more likely to develop stronger resistance faced with TP. In this regard, it can be said that users who are used to interacting with smart devices are more sensitive to paternalistic features (such as fewer or no options to change default settings) because they are more used to seize opportunities to regain threatened freedom (e.g., by changing default settings) and, consequently, show more reactivity (such as resistance; J. W. Brehm, 1966; Rochi, 2023) to regain control. Overall, the findings of the exploratory moderation analysis underscore the nuanced nature of the relationship between TP and technology resistance and highlight the importance of considering individual differences and contextual factors in understanding it.

4.3.6 Exploring impact on actual behavior

Thus far, this research has exclusively used behavioral intention and resistance as dependent variables. However, this may limit the scope of potential contributions, as empirical findings have indicated inconsistent strength in the intention–behavior relationship (Conner & Norman, 2022). Additionally, a fundamental goal of scientific inquiry should include the generation of managerially relevant knowledge. This requires clarity and actionability in the practical implications derived from research beyond a narrow focus on intention alone (Hulland & Houston, 2021). The author addressed this issue by applying experimental realism to the online surveys and asking participants to invest actual effort in making a post-survey decision to obtain more information about the presented product (Viglia et al., 2021).

The dependent variable, indicating the decision to seek additional product information, measures the propensity to invest time in reading and acquiring detailed product information. A binary coding scheme was used, with a “yes” response assigned a value of 1 and an otherwise assigned value of 0. For the binary character of the dependent variable, a binary logistic regression approach (conducted with IBM SPSS 28) was chosen to exploratively analyze the effects of behavioral intention, technology resistance, and TP on the likelihood of seeking more information about the presented smart vacuum cleaner concept. The overall model (including all three independent variables) was statistically significant when compared to the null model, ($\chi 2$(df 3) = 484.994, $p < .001$), and it correctly predicted 65% of cases. Behavioral intention ($p = .005$) was the only significant predictor (technology resistance $p = .520$; TP $p = .759$). The odds of behavioral intention were 1.301. Thus, as behavioral intention increases, the likelihood of seeking more information increases by approximately 30%.

It is notable that technology resistance and behavioral intention showed a strong correlation (−.753; $p < .001$), which may result in multicollinearity. Hence, these two independent variables (behavioral intention and technology resistance) were analyzed separately to overcome the potential issues of multicollinearity. Hence, two more logistic regressions were carried out to assess 1) the effect of TP and behavioral intention, and 2) the effect of TP and technology resistance on the likelihood of seeking more information about the presented smart vacuum cleaner. For 1), the model was statistically significant when compared to the null model, (χ^2(df 2) = 485.411, $p < .001$) and correctly predicted 58% of cases. Behavioral intention ($p < .001$) was the only significant predictor (TP; $p = .944$), and the odds of behavioral intention were 1.358. Thus, with increasing behavioral intention, the probability of seeking more information increased by about 36%. For 2), the model was statistically significant when compared to the null model, (χ^2(df 2) = 493.213, $p < .001$), and correctly predicted 63% of cases. Technology resistance ($p < .001$) was the only significant predictor (TP; $p = .542$). The odds of behavioral intention were .768. Hence, with increasing technology resistance, the probability of seeking more information decreases by about 23%. Table 30 provides an overview of all three logistic regressions.

Table 30: Logistic regression results (Study III.3)

Logistic regression	Regression coefficient (β)	p-value	Exp (β) (adjusted odds ratio)	Probability
Full model				
TP	.028	.759	1.028	.028
Behavioral intention	.264	.005	1.301	.301
Technology resistance	−.065	.520	.973	−.027
TP and behavioral intention only				
TP	.006	.944	1.006	.006
Behavioral intention	.306	<.001	1.358	.358
TP and technology resistance only				
TP	0.54	.542	1.056	.056
Technology resistance	−.264	<.001	.768	−.232

Discussion

For the effects of TP, behavioral intention, and technology resistance on actual survey participant behavior (seeking more information about the product), the results of the logistic regression analyses showed that both behavioral intention (positively) and technology resistance (negatively) significantly affected the probability of seeking more information. No empirical evidence was found that TP directly affected the probability of seeking further information about the product.

4.4 General discussion

This paper investigated how TP directly affects technology resistance and behavioral intention. It sheds light on the relationships between anthropomorphism, product autonomy, TP, behavioral intention, and technology resistance. It shows that the often-proposed positive effect of product autonomy and anthropomorphism on behavioral intention might not exist in all circumstances. Through TP, product autonomy and anthropomorphism indirectly affect behavioral intention negatively and resistance positively. This underlines the competitive mediation underlying this relationship of tension.

4.4.1 Contributions to theory

The present study makes important contributions to the literature. First, it enriches the field of smart technology adoption research by building on recent research on automation and the adoption and resistance of human-like technologies. It does so by fitting the concept of TP between technology adoption and resistance theories, and showing the relationships between them and TP.

Second, this work provides the first empirical evidence for the TP–behavioral intention/technology resistance relationship by relying on several independent datasets. It was demonstrated that the imminent rise of smart products poses a challenge to user acceptance. The findings revealed that TP varied among individuals, served as a deterrent to the adoption of smart products, and could increase technology resistance among users. Importantly, it was demonstrated that TP affects both behavioral intention and technology resistance directly.

It was also shown that anthropomorphism and product autonomy act as antecedents of TP, with both indirectly affecting TP and behavioral intention and resistance. Therefore, while anthropomorphic and highly autonomous products may enhance technology acceptance, both anthropomorphism and high autonomy increase perceived TP, which negatively impacts product adoption. This suggests that traditional theories of product acceptance may fall short when applied to smart products and encourages moving beyond established theories to deepen our understanding of how users perceive smart products.

4.4.2 Contributions to marketing practice

Despite the evident benefits of smart products, this emerging technology has characteristics that may hinder its widespread adoption or increase resistance. As the phenomenon of TP is relatively new and understudied in recent literature, this study contributes by pointing out that paternalistic features are an issue of concern in practice. Marketers should be aware of the paternalistic potential of their products and adapt their strategies accordingly. Marketers offering smart products can use the insights from moderation analysis to refine their segmentation and positioning strategies. One effective approach is to segment consumers based on their level of TP, distinguishing between high and low TP consumers. In addition, it may be worthwhile to increase the adaptability of smart products to ensure that they meet the needs of different types of consumers. For example, the greater adaptability of products for experienced users may lead to a lower perception of TP.

In particular, TP emerged as a robust predictor of behavioral intention and technology resistance. The moderation analysis provides insight into how different user characteristics influence the effects of TP on behavioral intention and technology resistance, which can also be used for product segmentation and positioning. Product involvement, domain-specific innovativeness, and experience with the product category should be considered. Strategies to increase product involvement may have a positive influence on the effect of TP on technology resistance. This is interesting, as some might suggest that increasing product involvement is a goal that marketers should pursue under all circumstances (e.g., through personalization or interactive product features), but this may be a double-edged sword when it comes to TP, as the effect of TP on technology resistance may be amplified by product involvement. In addition, the consideration of user-specific innovativeness may be valuable for practitioners, as increasing domain-specific innovativeness has a positive influence on the effect of TP on technology resistance. Users who have a strong understanding of domain-specific innovation may perceive TP more strongly than other users. Moreover, people who already have experience interacting with smart vacuum cleaners tend to have stronger perceptions of TP and therefore higher technology resistance to the smart product. Recognizing the importance of user attributes in marketing strategies may help practitioners mitigate the negative effects of TP, thereby reducing technology resistance and increasing behavioral intention to use newly developed innovative smart products.

4.4.3 Limitations and future research

The present findings have the potential to stimulate research that is both intriguing and relevant. Existing studies have highlighted the negative effects associated with smart products, including Rochi (2023), Rochi et al. (2024), and F. Schweitzer and van den Hende (2016). It would be valuable to investigate the extent to which these sentiments are intensified among consumers with high perceptions of TP, and whether any interventions or changes in product design can mitigate the negative effects of TP. In addition, given the growing interest in anthropomorphizing technologies (Blut et al., 2021), it would be worthwhile to further explore the tension between anthropomorphism, TP, and behavioral intention or technology resistance. It might be valuable to know under what circumstances framing smart products as social entities through anthropomorphism leads to increased TP and consequently dampens (increases) behavioral intention (technology resistance).

More context-specific research may augment the value of this research stream. It may be worth investigating how perceptions of TP change with different utilitarian or hedonic motivations for use, as the intention to use a technology is influenced by the technology's utilitarian and hedonic values (L. Xu et al., 2012). As smart products operate according to the rules programmed into them, the question arises as to whether TP depends on those who set the operating rules (algorithms) for these products (Spiekermann & Pallas, 2006). In this context, software engineers, companies, and government agencies may be the main actors associated with TP

(Millar, 2015). It would be worth investigating how a user's awareness that a smart product only implements rules programmed by humans affects perceptions of TP.

The findings of Studies III.2 and III.3 that increased product autonomy leads to less technology resistance are interesting. These results contradict the developed hypotheses and recent theoretical foundations. It might be interesting to replicate these results or to determine why and how product autonomy reduces technology resistance instead of increasing it.

Like all scientific work, this study has several shortcomings. First, this study was conducted in Germany. Consumer behavior and attitudes toward smart technologies can vary significantly due to cultural nuances; therefore, future research is recommended to confirm these findings in different cultural settings. Different cultural characteristics in dimensions such as individualism or power distance (Hofstede, 2011) may influence perceptions of TP; therefore, generalizing the findings should be done with caution. Second, this study relies on data collected through online surveys. When the interaction between researchers and participants is predominantly remote and anonymous, as is the case with online surveys and experiments, incorporating a realistic scenario may be challenging (Viglia et al., 2021). Future research attempts in this domain should not (only) rely on online surveys but include real-world experiments with manipulated real smart products to introduce real interaction scenarios to study participants.

CHAPTER

5

OVERALL RESULTS, CONTRIBUTIONS, CONCLUSIONS, AND LIMITATIONS OF THIS DISSERTATION

5. Overall results, contributions, conclusions, and limitations of this dissertation

5.1 Overall results

The primary goal of this thesis was to develop a thorough conceptualization and assessment of TP in the context of existing research. To do so, a thorough review of how TP was defined, conceptualized, and measured in the past (addressing Research Question I) served as the basis for an updated definition of TP (Research Question II) and the development of a theoretical model of how TP affects behavioral intention and technology resistance and how it fits between these theoretical models (Research Question III). The developed measurement scale (Research Question IV) served as the underpinning for the further investigation of the antecedents and consequences of TP (Research Question V), how TP settles in the canon of usage intention and technology resistance (Research Question VI), and how its effects are mediated or moderated by certain constructs (Research Question VII).

The semi-systematic literature review in Paper I laid the groundwork for comprehending TP, shedding light on deficiencies in the prior understanding of TP and the absence of measurement methods. This revealed a scarcity of literature, as TP has been the subject of only a minor number of publications so far. The first conceptualization of TP was by Spiekermann and Pallas (2006), at a time when context-aware and autonomous technologies seemed to be visions of the future. While certain aspects of TP, such as compromised autonomy due to independently acting smart products, were more present in the literature, other effects, such as the negative consequences of excessive user support, were not. In Paper I, the suggested multiplicative nature of TP has several implications. First, the paternalistic features of smart products may complement and mutually reinforce perceived TP. Second, TP develops only when all dimensions are perceived. The review uncovers the effects of product smartness on adoption through TP, challenging the assumption that "the more support the better" is always true. The author developed a model illustrating that TP and its dimensions have both direct and indirect effects on technology acceptance and resistance (shown in Figure 4).

The main goal of Paper II was the development of a measurement scale for TP. A series of five qualitative and quantitative studies explored the concept of paternalism within the context of human–computer interaction. The interviews in Study II.1 uncovered three sub-dimensions of perceived TP, aligning closely with its outlined definition. The two main results regarding the further specification of TP were as follows: First, as perceived by users, TP is a multi-dimensional construct (comprising autonomy cut, overruling prospects, and welfare intention of the smart technology). Second, the respondents presented a limited number of statements pertaining to the significance of product autonomy in the perception of TP. This phenomenon may be ascribed to the prevailing assumption that all technologies evaluated in the interviews were inherently characterized as (at least partly) autonomous. This distinction supports the contention that product autonomy is a prerequisite for TP rather than an incremental dimension.

Based on this conceptualization, Studies II.2 and II.3 served for item generation and measurement scale specification. A collaborative effort was undertaken with experts and consumers to validate all items generated. Consequently, Studies II.4 and II.5 empirically underpinned the results of the qualitative research attempts, resulting in a three-dimensional 16-item measurement scale for TP. Further analysis showed strong nomological validity, as the TP scale correlated with related constructs.

The consecutive empirical analyses in Paper III provided further insights into the causes of TP, its consequences, and its moderators. Study III.1 investigated how TP affects behavioral intention and the roles played by anthropomorphism and product autonomy as antecedents. It showed that TP affected both behavioral intention and technology resistance directly, and it served as a mediator between anthropomorphism and product autonomy and behavioral intention. Study III.2 partly replicated the results of Study III.1, namely, the role of anthropomorphism as an antecedent of TP. In contrast to Study III.1, no empirical evidence was found that product autonomy served as an antecedent of TP in this study. Study III.3 combined the SEMs of Studies III.1 and III.2, as it included both technology resistance and behavioral intention as dependent variables. This study successfully replicated the previously observed impacts of TP on both technology resistance and behavioral intention. Regarding the impact on technology resistance, it identified a competitive mediation effect: product autonomy directly reduced technology resistance while also indirectly increasing it through TP. This pattern applied similarly to anthropomorphism. Although there was no direct significant effect of anthropomorphism on technology resistance, this study revealed a mediation effect through TP, leading to complete mediation.

In the exploratory moderation analysis, the results revealed that anthropomorphism, product involvement, level of domain-specific innovativeness, and ownership of a product from the same category moderated the effect of TP on technology resistance. In contrast, no evidence was found that metaphorical thinking moderated the relationship between TP and technology resistance.

Concerning the impacts of TP, behavioral intention, and technology resistance on participants' actual behavior in seeking more information about the product, logistic regression analyses indicated that behavioral intention positively influenced the likelihood of seeking more information, while technology resistance had a negative impact. However, there was no empirical support for the notion that TP influenced the probability of seeking further information about the product.

5.2 Overall theoretical contribution

This dissertation contributes to the body of knowledge on technology adoption and resistance in several ways. It shows, both conceptually and empirically, that the phenomenon of TP affects the adoption and resistance behavior of users. It identifies gaps in the literature, particularly in relation to smart technologies and their paternalistic aspects, emphasizing the academic implications of these omissions. It extends relevant theories by clarifying that the phenomenon of TP affects both adoption intention and resistance.

Paper I contextualizes TP within theoretical models of acceptance and resistance, revealing overlooked factors contributing to technology resistance and lower adoption of smart products. Through a semi-systematic literature review, it identifies shortcomings in existing conceptualizations of TP and proposes a new model that integrates psychological reactance theory. This model enhances the understanding of smart product perception and underscores the critical yet understudied nature of TP. Paper I also identifies TP dimensions and their multiplicative characteristics, introducing a new factor that influences perceptions of smart products. This contributes significantly to the literature, particularly as past research has primarily focused on the positive aspects of smart products, neglecting potential negative influences (Castellion & Markham, 2013; Talke & Heidenreich, 2014).

This study conceptualizes TP as a focal point, enabling scholars to conduct a comprehensive analysis of smart product design and its impact on consumer attitudes. It facilitates the extraction of nuanced insights into the optimal configuration of smart products. Furthermore, it enhances existing research on smart product adoption by illustrating that excessively accommodating certain product features can affect product valuation, potentially leading to negative consumer perceptions. This research promotes a more comprehensive approach to smart product development that recognizes the dual implications of smart product attributes.

Paper II aims to advance the understanding of TP by incorporating recent research insights to conceptualize it appropriately and develop a valid and reliable measure. This contributes to a comprehensive understanding of smart product adoption and resistance. The paper delves into the multi-dimensional structure of TP and its relationships with other constructs in the field. This is particularly relevant due to the scarcity of explicit research on TP, with related constructs often being explored instead. The validated scale can be applied across disciplines studying the psychological aspects of smart technology use. Additionally, the paper challenges prevailing definitions and assumptions, such as regarding product autonomy as a prerequisite for TP rather than as a dimension of it. It offers empirical evidence for the TP–technology adoption relationship and expands the understanding of TP's influence on smart technology acceptance. Moreover, it pioneers the creation of a scale to gauge TP, which is beneficial for both research and practical applications, paving the way for future investigations into TP across diverse populations and settings. This contributes to research on emerging technologies by providing a robust measurement tool for TP, ensuring consistent outcomes and broadening the understanding of its universal and context-specific aspects.

Paper III contributes to the growing field of research on smart technologies, building on recent investigations into their adoption and resistance. This paper introduces empirical evidence demonstrating that TP significantly impacts adoption intention and technology resistance, thereby influencing the adoption of smart technologies. It contributes to theory testing by examining the relationships between TP and other constructs within the nomological network. Additionally, it enhances our understanding of the complex interplay between TP and various constructs and variables, elucidating underlying mechanisms and causal pathways. For example, this study revealed that while product autonomy and anthropomorphism typically increase behavioral intention, they also induce TP, offsetting their benefits, at least partially. By demonstrating that both product autonomy and anthropomorphism may increase TP, thereby indirectly affecting product adoption negatively and technology resistance positively, this research emphasizes that an increase in product smartness or autonomy does not necessarily enhance adoption intention due to higher product value.

To summarize all the contributions of this thesis on a global level, the author draws on a framework by MacInnis (2011), which provides a typology of conceptual contributions. MacInnis (2011) divided conceptual contributions into eight specific conceptual objectives (those in **bold** are covered in this thesis):

1) **Identifying**: Researchers who contribute by identifying aim to introduce a construct, theory, procedure, field, discipline, or aspect of science that has not yet been fully recognized or seriously studied. The goal is to highlight and establish areas that are still emerging or underexplored. MacInnis (2011, p. 143) paraphrases it as "seeing that something exists."
2) **Revising**: Revising involves reevaluating or adopting a new perspective on something that has already been identified. While identifying aligns with the logic of discovery, revision considers empirical evidence about the identified entity and modifies it accordingly. Contributions based on revision derive insights from alternative viewpoints. MacInnis (2011, p. 143) paraphrased it as "seeing what has been identified in a different way."
3) **Delineating**: This entails the goal of detailing, articulating, charting, describing, or depicting an entity. Often, this charting helps researchers consider how the entity they study relates to the broader conceptual world around it. MacInnis (2011, p. 144) paraphrased it as "detailing an entity."
4) **Summarizing**: The aim of summarization is to assess, digest, recap, and condense existing knowledge into a concise set of key points. Summarization often relies on empirical evidence to draw conclusions about established information, aligning with the context of justification. Conceptual papers focused on summarization are frequently referred to as review papers or critical syntheses. MacInnis (2011, p. 144) paraphrases it as "seeing the forest for the trees".
5) **Differentiating**: Differentiation entails conceptual progress that enhances understanding by distinguishing, parsing, dimensionalizing, classifying, or categorizing an entity (such as a construct) under investigation. MacInnis (2011, p. 145) paraphrases it as "seeing differences".
6) Integrating: Integration merges aspects of both revision and summarization by adopting a new viewpoint and encompassing a holistic view. However, it goes beyond merely outlining existing findings by transforming known and theorized elements into a completely new construct. It connects previously distinct phenomena into a novel, simplified, and higher-order perspective on their relationships. It synthesizes all parts into a cohesive whole, leading to comprehensive theories that reconcile contradictions and yield

fresh insights, offering a streamlined yet nuanced understanding of complexity. MacInnis (2011, p. 146) paraphrased it as "seeing the simplicity from the complex."

7) Advocating: Advocacy entails arguing to justify or support a particular conclusion. In this role, researchers endorse or promote a specific viewpoint or course of action, effectively acting as guides who use a compass to steer the direction forward. MacInnis (2011, p. 147) paraphrased it as "endorsing a way of seeing."
8) **Refuting**: In contrast to advocacy, refuting entails argumentation that seeks to rebut, challenge, dispute, or contest a specific perspective. MacInnis (2011, p. 147) paraphrased it as "rebutting a way of seeing."

The first conceptual contribution of this thesis was to **identify** the construct of TP. In Paper I, a novel framework in which TP is embedded in technology adoption and resistance theories was developed to show the reader a new perspective on product smartness and its potential negative effects. The author provides arguments through a literature review and by pointing to aligned research areas in which the construct of TP is important, not fully recognized, and understudied. Additionally, Paper I guides future research through propositions, indicating novel research questions fostered from the identification of TP as a construct to focus on and by providing a first conceptual framework with cause-and-effect relationships.

Second, Paper II **revises** the conceptualization of TP from previous research (and Paper I). The author points out that the original definition of TP needs a reconfiguration, as Paper II underlines – through qualitative and quantitative approaches – and that product autonomy needs to be considered as an antecedent of TP rather than a subdimension of the construct.

Third, the author **delineates** and **differentiates** the construct of TP by showing how it relates to the broader conceptual world. Papers II and III provide empirical evidence of how TP interrelates with antecedents, consequences, and moderators. Furthermore, the author offers a differentiation between TP and other related theories and concepts.

Fourth, Paper I **summarizes** and consolidates the literature on technology adoption and resistance in the context of smart products. With an organizing framework, the author provides a clear, accurate, and relevant conclusion on how and why TP affects behavioral intention and technology resistance. The result is the reduction of the body of knowledge to a convenient set of key aspects.

Finally, all three papers **refute** the perspective that the more autonomy and human-likeliness a smart product has, the greater its usefulness and the resulting adoption intentions should be. Paper I does this by developing the conceptual framework of how TP affects behavioral intention and resistance. Paper II provides initial empirical evidence that TP affects behavioral intention and resistance. Paper III provides further evidence of the competitive mediation of product autonomy and anthropomorphism, challenging the assumption that higher product autonomy and more emphasis on product anthropomorphism increase product acceptance per se. This is no longer true under all circumstances when it comes to intelligent product adoption.

5.3 Overall managerial implications

This study provides practical insights for smart product developers, managers, and governmental institutions. First, developers and managers should consider TP as a key factor influencing technology resistance and the acceptance of smart products. The findings of Paper I emphasize the impact of TP on technology adoption and resistance and suggest ways to mitigate issues such as perceived restrictions on freedom. Introducing customization options, interrupting autonomous processes, and configuring assistance levels can enhance user acceptance. This study underscores the importance of tailoring smart product design to individual characteristics, considering factors such as user experience and task familiarity. It also offers valuable considerations for managers implementing smart products in professional environments and cautions against potential consumer backlash related to TP.

Additionally, Papers II and III highlight the significance of addressing perceived TP in marketing strategies for successful smart product adoption, providing a validated measurement scale for assessing paternalistic potential and nomological validation. The utilization of the scale provides practitioners with a diagnostic tool for assessing TP. This allows for a more accurate identification of TP influencing user behavior. With the ability to measure TP, practitioners can better target interventions for smart products, aiming to address TP specifically. In marketing and product development, insights gained from the structural equation models in Paper III can inform the design and marketing strategies of products, services, and customer experience. This leads to the development of products that better meet consumer needs and preferences, resulting in increased customer satisfaction and loyalty. The developed scale aids in finding a balance between user support and avoiding overwhelming users, offering guidance for developing adaptive and less paternalistic smart products, and finding the "sweet spot" between user support and paternalistic behavior.

Marketers need to recognize the paternalistic potential of the products they promote to effectively tailor their strategies. It is suggested that marketers of smart products use insights from the moderation analysis to refine segmentation and positioning strategies. A prudent approach is to segment consumers based on their TP levels, for example, distinguishing between high and low TP consumers. It is also advisable to increase the adaptability of intelligent products to meet the different needs of consumers. For example, increasing adaptability for experienced users can mitigate the perception of TP. Furthermore, product involvement, domain-specific innovativeness, and experience with the product category warrant consideration. For instance, strategies to increase product involvement, while generally favorable, may inadvertently amplify the effect of TP on technology resistance. This underscores the nuanced nature of TP's impact. Moreover, addressing user-specific innovativeness may be valuable for practitioners because higher domain-specific innovativeness positively influences the effect of TP on technology resistance. Thus, users with a strong understanding of innovation may perceive TP more acutely. Individuals with prior experience interacting with a product category tend to show heightened perceptions of TP and, consequently, increased technology resistance toward the smart product. Recognizing the importance of user attributes in marketing strategies may help practitioners mitigate the negative effects of TP, thereby reducing technology resistance and increasing behavioral intentions toward newly developed innovative smart products.

5.4 Overall limitations and future research

The research outlined in each paper forming this dissertation is constrained by various specific and distinct limitations, all of which are addressed in the conclusion chapter of each paper. Nonetheless, the main limitations of the overall dissertation are outlined below.

This thesis has various limitations that warrant discussion. Some of these limitations serve as foundations for the proposed areas of future research. First, this work is based on self-reported correlational data from a single cultural and national setting. Self-reported data are subject to memory, social desirability, and other biases (Podsakoff et al., 2003). To overcome the weaknesses associated with relying solely on self-reported data in a study, researchers may adopt experiments with manipulated smart products to track the actual behavior of study participants.

Further, data derived from a single cultural and national setting in a study can introduce several weaknesses and limitations that may impact the generalizability, relevance, and applicability of the research findings (Arnett, 2016; Greenfield, 1997; Henrich et al., 2010). For example, people's reactions to governmental threats differ by culture (Ng et al., 2021). Cultural factors can also affect the perception of personal autonomy (Rudy et al., 2007) and therefore the perception of TP. Hence, follow-up studies could make significant contributions to the existing body of knowledge by comparing results from different cultural environments. The data for the studies of Papers II and III were collected from the population in Germany, a country with relatively high smart product market penetration (Statista, 2022). This suggests that the participants were already accustomed to interacting with smart technologies or had at least had some contact with them. Future studies could delve into this subject using a culturally diverse sample with variations in age, education, and proficiency in smart technology. Consumers new to using smart technology might feel a stronger sense of TP, possibly due to their limited understanding of the technology's inner workings and associated anxiety, potentially leading to more serious consequences.

Identifying ways to measure TP based on physiological data and reducing it adaptively may provide further information about how TP affects user choices. New technologies, such as specific augmented reality or virtual reality devices, can have built-in sensors to capture such data across usage contexts (Au et al., 2023; Rauschnabel et al., 2022). It would also be beneficial to understand how different combinations of the three dimensions lead to differential behavioral outcomes or degrees of TP. It would be informative to understand how single dimensions interact and how these dimensions affect TP from an isolated point of view. In Paper II, the authors developed a table describing potential application areas of the newly developed measurement scale. Future research could examine how technology attributes, personal user attributes, and situational attributes affect perceptions of TP. To highlight this, the author added Table 31 (initially included in Paper II) to underline potential future research avenues in different contexts.

While this manuscript focuses on perceptions of TP at the user level, it might be interesting to understand whether users realize that the real patrons behind paternalistic technologies are the developers, marketers, and governmental bodies who develop the underlying algorithms or introduce overarching paternalistic regulations (Spiekermann & Pallas, 2006). This awareness may affect the perception of TP. With the newly developed measurement scale, further research on how TP affects user behavior is possible and desirable. For instance, Rochi (2023) proposed that the effect of TP on user behavior was moderated by the amount of information provided, information solicitation, and adaptability of the product. With the new measurement scale, the author paved the way for testing these propositions with future research attempts.

Moving beyond the individual human–computer interaction research environment, where and how can the concept of TP further play a role? Is it possible that brands can be perceived as paternalistic? If products from certain brands act paternalistically, does this influence perceptions of the brand? TP extends beyond the realm of human–computer interaction and can potentially influence broader consumer perceptions, brand relationships, and even societal norms. If a brand's products exhibit paternalistic behavior, it may influence consumers' perceptions of the brand. Examples include a smartphone that prioritizes notifications based on perceived importance or a smart home device that adjusts settings for efficiency without user input. If these actions align with user expectations and values, the brand may be perceived as thoughtful and intelligent. However, if they overstep or misinterpret user desires, the brand could be viewed as paternalistic.

In blue-collar sectors, which typically involve manual labor or manufacturing jobs, TP can manifest through automated systems that direct work processes, safety protocols, and task prioritization. This phenomenon is called “management by algorithm” (Knudsen et al., 2021). While this approach can enhance efficiency and safety, it also raises concerns about workforce autonomy and skill development, potentially leading to a less motivated workforce (Granulo et al., 2024) and negative emotions (M. K. Lee, 2018; M. K. Lee et al., 2015).

More generally, TP may affect business environments by centralizing decision-making in AI systems. Paternalistic technology potentially shifts power dynamics within organizations, diminishing middle management roles and altering traditional hierarchies. It can shape the company culture, possibly leading to a more data-driven and efficiency-focused environment but at the risk of undervaluing human intuition and interpersonal relationships, which some may find dystopic. Hence, TP raises ethical questions about privacy, consent, and the extent to which employers should have control over their employees’ work processes and data.

On a societal level, the widespread adoption of paternalistic technology raises ethical questions about autonomy, consent, and the role of technology in our lives. It prompts a reevaluation of how we interact with technology, the power dynamics at play, and the need for ethical frameworks and regulations to ensure that technology serves humanity's best interests without undermining individual autonomy.

As lawmakers confront the challenges posed by the widespread adoption of potential paternalistic technology, their response should be multifaceted and aim to protect individual autonomy while leveraging the benefits of technological advancements, such as by creating laws that define the limits of AI and technology and ensuring that autonomous decisions are made transparently and with user consent. Moreover, governmental bodies may mandate that companies explain their technology's decision-making processes and data usage, possibly through explainable AI principles. It may also be fruitful to incentivize ethical design practices that prioritize human values and well-being in technology development or to promote partnerships across sectors to develop ethical standards and best practices for technology use. Finally, to track the impact of such technologies, a continuous evaluation of the social and ethical impacts of paternalistic technologies might be necessary to guide regulatory updates.

This thesis lays the foundation for understanding how TP affects human–computer interaction and society beyond. With this work, further research can quantify the effects of this phenomenon on several aspects on individual, organizational, and societal levels.

Table 31: Possible future applications and research avenues for the concept of TP (taken from Paper II; Rochi et al., 2024)

Context	Application
Technology focused: How does welfare intention moderate the impact of TP?	Achieving the right balance between transparency and support is crucial for smart product acceptance (Rochi, 2023; Venkatesh, 2022). Inadequate transparency can result in mistrust (Kizilcec, 2016) or a perceived loss of personal control (Botti & Iyengar, 2006), whereas excessive support may lead to information overload (Schein & Rauschnabel, 2022). Additionally, reciprocal communication between the user and the smart product (interactivity) negatively affects perceived intrusiveness (Lucia-Palacios & Pérez-López, 2021), and unsolicited advice is valued less than voluntary and requested advice (van Swol et al., 2017). This is also true for smart products, where unsolicited advice can lead consumers to ignore technology recommendations and can trigger boomerang effects (Feng & Magen, 2016). Hence, Rochi (2023) proposed that providing more support initially enhances perceived usefulness, but there is a point where it reaches a peak and starts to decline, creating an inverted U-shaped effect. **This interrelationship between the welfare dimension of TP and the other two dimensions needs further investigation.**
Technology focused: How do smart product characteristics drive TP?	**Adaptability**: Designing interfaces that allow users to regain control when necessary can reduce distrust and helplessness (Brell et al., 2019). Such designs increase perceived self-control (Milchram et al., 2018) and decrease perceived disempowerment (de Bellis & Johar, 2020). Incorporating personalization and customization features enhances user trust in smart products (Ghazali et al., 2018a). **Hence, whether adaptability plays an influencing role in the perception of TP requires further investigation.**
User focused: How do user characteristics drive TP?	**Experience**: Balancing default personalization and user-controlled personalization of smart products relies on considering individual needs, characteristics, and the context of use and usage expertise, which can all affect perceived usefulness or usage intention (Attié & Meyer-Waarden, 2022; Logg et al., 2019; Venkatesh, 2022; Wang et al., 2018). **Hence, whether user experience (both specific smart product experience and general smart product experience) and task experience influence the perception of TP requires further investigation.** **Emotional and psychological factors**: Recent research endeavors in technology adoption have introduced novel elements, such as user well-being and happiness (Attié & Meyer-Waarden, 2022), trust (Vimalkumar et al., 2021), self-construal (Aljukhadar et al., 2017), and discomfort and insecurity (Chang & Chen, 2021) as factors influencing adoption behavior. **To understand the effects of TP, it is necessary to understand how these emotional factors (are) influence(d by) the perception of TP.** **Age**: As our results indicate that TP is uncorrelated with age, suggesting that TP can be experienced across age groups, future research could explore whether the antecedents of TP differ. **It would be informative to understand whether younger consumers tend to feel paternalized if hedonic value decreases, or whether older consumers have stronger usage routines, meaning a disruption of routines through protective features might trigger TP.**
Situation focused: How do situational characteristics and context drive TP?	To further understand how TP arises, it is necessary to investigate under which situations users perceive TP. Certain characteristics of situations and contexts may play a key role, such as the **unusualness, perceived danger, and familiarity** of a situation (Venkatesh, 2022). These aspects are strongly connected to the above-mentioned user-focused aspects, and they should be investigated together. It is important to understand whether user awareness about "**the real patrons**" (Spiekermann & Pallas, 2006, p. 12)—that is, that the smart product is not the patronizing entity but the company that introduced the product—affects the perception of TP.

5.5 Conclusion

Paternalism manifests in diverse relationships, spanning from family dynamics to governmental policies and, increasingly, in interactions between users and smart technologies. Despite its pervasive nature, TP has received limited attention in recent scholarly discourse. As technological advancements continue to embed smartness, autonomy, and human-likeness into various products and systems, the significance of this phenomenon is becoming increasingly apparent. This dissertation has demonstrated the conceptualization and measurement of TP and its profound influence on technology adoption and resistance. Notably, conventional strategies aimed at enhancing product adoption, such as anthropomorphism and increased autonomy, may inadvertently heighten perceptions of TP, challenging the assumption of their efficacy in bolstering product acceptance.

This dissertation serves as a catalyst for future research endeavors by delineating avenues for investigating TP in diverse contexts, including culturally varied environments, workplace dynamics, and domestic settings. By shedding light on these mostly unexplored areas, scholars can deepen their understanding of the nuanced manifestations of TP and its implications for technology adoption.

Ultimately, it is envisaged that this dissertation will spark a surge of scholarly interest and collaborative efforts within the scientific community, leading to a more comprehensive understanding of TP and innovative approaches to addressing it. Through concerted research attempts, we can endeavor to ensure the widespread acceptance and utilization of smart products while mitigating the potentially adverse effects of TP.

APPENDICES

Appendices

Appendix – Paper I – Chapter 2

Table 32: Literature review conceptual framework (in alphabetical order)

No.	Source	Limiting Condition	Overrule Condition	Auto-nomy Condition	Welfare Condition	Potential Modera-tors	Research stream
1	Aguirre et al. (2015)				x		Retail Management
2	Ameen et al. (2021)		x				Consumer research
3	Antifakos et al. (2005)			x			HCI
4	Appelgren (2018)				x		Journalism
5	Appelgren (2019)				x		Journalism
6	Barria-Pineda et al. (2019)				x		HCI
7	Behmann and Wu (2015)		x				HCI
8	de Bellis and Johar (2020)		x				Retail Management
9	Boeck et al. (2011)	x					HCI
10	Brell et al. (2019)		x	x			Ergonomics
11	Broadbent et al. (2009)					x	HCI
12	Buchanan et al. (2016)	x					Energy Management
13	Bunt et al. (2012)				x		HCI
14	X. Chen et al. (2021)			x			Consumer research
15	Coyle et al. (2012)	x					HCI
16	Cronin (2010)		x				HCI
17	Dickenberger and Gniech (2019)	x					PRT
18	Dietvorst and Bharti (2020)	X					Psychology
19	Dietvorst et al. (2018)	x					HCI
20	Dworkin (2020)				x		Paternalism
21	Dzindolet et al. (2002)			x			Ergonomics
22	Ehrenbrink et al. (2016)			x			HCI
23	Ehrenhard et al. (2014)	x					Elderly Care
24	Ekman et al. (2018)			x			HCI
25	Feng and Magen (2016)				x		Social Sciences
26	Fitzsimons and Lehmann (2004)				x		Marketing Management
27	Gaudiello et al. (2016)	x					HCI
28	Ghazali et al. (2017)					x	HCI
29	Ghazali et al. (2018a)					x	HCI
30	Ghazali et al. (2018b)					x	HCI
31	Ghazali et al. (2019)					x	HCI
32	Gino (2008)				x		Organizational Behavior
33	Glass et al. (2008)		x		x	x	HCI
34	Gönül et al. (2006)					x	HCI
35	Hanus and Fox (2017)					x	Marketing Management
36	Hardian et al. (2006)			x		x	HCI
37	T. Hargreaves and Wilson (2017)	x	x				HCI
38	Helbing et al. (2019)				x		Product Design
39	Henkens et al. (2021)			x			Marketing Management
40	Hock et al. (2019)		x				Autonomous Cars
41	M.-H. Huang and Rust (2018)					x	HCI
42	Josten et al. (2017)			x			Autonomous Cars
43	Kayande et al. (2009)			x			Information Systems
44	Kinder et al. (2008)		x				HCI
45	Kizilcec (2016)				x		HCI

46	Köbis and Mossink (2021)		x				HCI
47	König and Neumayr (2017)	x					Consumer research
48	Kulesza et al. (2013)				x		HCI
49	Kulesza et al. (2015)				x		HCI
50	Langer and Landers (2021)		x				HCI
51	Lawrence (2006)		x				HCI
52	G. Lee and Lee (2009)				x		HCI
53	B. Y. Lim and Dey (2009)				x		HCI
54	J. S. Lim and O'Connor (1996)					x	HCI
55	Link et al. (2013)		x				Leadership
56	Litterscheidt and Streich (2020)			x			Education
57	Logg et al. (2019)					x	HCI
58	Mani and Chouk (2017)	x					Consumer research
59	Mani and Chouk (2019)	x					Consumer research
60	Meissner et al. (2020)		x				HCI
61	Michler et al. (2020)		x	x	x		Product Management
62	Mikulincer (1988)					x	Social Sciences
63	Milchram et al. (2018)	x	x				Energy Management
64	Millar (2015)		x				Product Management
65	Millecamp et al. (2019)				x		HCI
66	Miron and Brehm (2006)					x	PRT
67	Moser (2017)	x					Energy Management
68	Murray and Häubl (2009)				x		HCI
69	Narayanan et al. (2018)					x	HCI
70	Newman et al. (2020)		x				Organizational Behavior
71	Nikolaidis et al. (2015)				x		HCI
72	E. Park et al. (2018)	x					HCI
73	Pollak et al. (2020)	x					HCI
74	Poursabzi-Sangdeh et al. (2021)	x					HCI
75	Qiu and Benbasat (2009)					x	Information Systems
76	Rader and Gray (2015)				x		HCI
77	Raff and Wentzel (2018)			x			HCI
78	Rijsdijk and Hultink (2009)	x					Product Management
79	Rödel et al. (2014)	x		x			Product Management
80	Roubroeks et al. (2010)	x					HCI
81	Roubroeks et al. (2009)			x		x	HCI
82	Royakkers and van Est (2015)					x	HCI
83	Sankaran et al. (2021)		x				Ethics in IT
84	Schein and Rauschnabel (2021)			x			HCI
85	F. Schweitzer and van den Hende (2016)	x	x				Consumer research
86	F. Schweitzer et al. (2019)	x					Marketing Management
87	Sharan and Romano (2020)	x		x			HCI
88	Sørensen and Schmidt (2016)		x		x		HCI
89	Souka et al. (2020)		x				Consumer research
90	Sovacool et al. (2020)	x					Energy Management
91	Spiekermann and Pallas (2006)	x					Ethics in IT
92	Stein et al. (2019)	x	x	x	x		Information Systems
93	Sutherland et al. (2016)				x		HCI
94	Swar et al. (2017)	x					HCI
95	Tracey et al. (1989)				x		PRT
96	van Swol et al. (2017)					x	Communication
97	N. Wang et al. (2018)				x		HCI
98	Waytz et al. (2014)	x	x	x		x	Social Sciences

99	Weiser et al. (2016)					x	Autonomous cars
100	Wiebe et al. (2016)				x		HCI
101	Wieland et al. (2009)				x		HCI
102	Wilson et al. (2017)		x				Consumer Research
103	Wirtz et al. (2018)	x					Information Management
104	Wong et al. (2022)		x				Service Management
105	Xue (2019)					x	HCI
106	R. Yang and Newman (2013)	x					HCI
107	Yost et al. (2019)		x			x	Marketing
108	L. Zhang et al. (2021)					x	Social Sciences
109	Złotowski et al. (2015)			x			HCI
110	Złotowski et al. (2017)					x	HCI

Appendix – Paper II – Chapter 3

Table 33: Validation study participants (Study II.3)

	Expert view			
No.	**Pseudonym**	**Profile**	**Category**	**Gender**
1	“Steve”	Heads a Chair of Human-Machine Interaction at a German university.	Science	M
2	“Marcus”	Leads a research group at a German university. He is interested in the design of secure systems and human computer interaction.	Science	M
3	“Max”	Teaches and conducts research in the field of people and business analytics. Before his appointment at university, he was a senior business analyst, responsible for the data-driven optimization of products.	Science / practice	M
4	“Stephanie”	Researches and teaches in the field of business and organizational psychology. Among others, she focuses on health and stress in modern work environments. As a freelance consultant, she works with (inter)national companies to link theory and practice.	Science / consulting	F
5	“Peter”	Involved in numerous projects studying user experience for immersive technologies. His research focuses on the design and application of augmented reality, virtual reality and mixed reality enhanced experiences and the impact on consumer psychology and behavior.	Science	M
6	“Patrick“	UX/UI connectivity expert at a German automotive manufacturer	Practice	M
7	“Gustavo”	Researcher with focus on the interplay of people and technology. Member of the management board of a research institute.	Science	M
8	“Lydia”	Investigates the role of digital technologies in social fields: Digital Work, Assistive Technologies, Aging; Conducts conceptual research in the field of technology assessment; expert in qualitative research methods	Science	F
	Consumer view			
No.	**Pseudonym**	**Profile**	**Category**	**Gender**
9	“Liam”	Student	Education	M
10	“Noah”	Student	Education	M
11	“Olivia”	Student	Education	F
12	“Emma”	Student	Education	F
13	“Charlotte”	Student	Education	F
14	“Amelia”	Business consultant	Practice	F
15	“Ava”	Dept. Lead in healthcare industry	Practice	F
16	“Sophia”	Chemical engineer	Practice	F
17	“Oliver”	Paramedic	Practice	M
18	“Elijah”	Supply chain manager in pharma industry	Practice	M
19	“James”	Startup consultant	Practice	M
20	“William”	Controller IT industry	Practice	M
21	“Benjamin”	Adolescent Therapist	Practice	M
22	“Lucas”	Finance Manager in mechanical engineering industry	Practice	M
23	“Henry”	Startup Founder and CEO	Practice	M
24	“Theodore”	CEO in tourism industry	Practice	M

Note: F = female; m = male

Table 34: List of all items used (Paper II)

Scale	Code	Items (English)	Items (German)	Study	Source
Technology paternalism	auto1	The system restricts my freedom.	Die Technologie schränkt meine Freiheit ein.	EFA Study II.4 CFA Study II.5	Study II.1 Study II.2 Study II.3
	auto2	The technology makes me lose freedom of choice.	Durch die Technologie verliere ich an Entscheidungsfreiheit.		
	auto3	The technology overrides my desires.	Die Technologie setzt sich über meine Wünsche hinweg.		
	auto4	The technology disregards my wishes.	Die Technologie missachtet meine Wünsche.		
	auto5	The technology decides against my will.	Die Technologie entscheidet gegen meinen Willen.		
	auto6	I feel like I'm externally controlled by the technology.	Ich habe das Gefühl, von der Technologie kontrolliert zu werden.		
	auto7	The technology is authoritarian.	Die Technologie ist autoritär.		
	over1	The final decision is up to the technology, even if I don't want it to be.	Die finale Entscheidung liegt bei der Technologie, auch wenn ich das nicht möchte.		
	over2	I can't overrule the decisions of technology.	Ich kann die Entscheidungen der Technologie nicht überstimmen.		
	over3	I can't get around the choices of technology.	Die Entscheidungen der Technologie kann ich nicht umgehen.		
	over4	The technology requires that I submit.	Die Technologie erfordert, dass ich mich unterwerfe.		
	over5	The technology forces me to accept its decisions.	Die Technologie zwingt mich, ihre Entscheidungen zu akzeptieren.		
	wel1	The technology ensures that I follow rules.	Die Technologie stellt sicher, dass ich Regeln einhalte.		
	wel2	The technology wants the best for me, even if that means overruling me.	Die Technologie will das Beste für mich, auch wenn das bedeutet, dass ich von ihr übergangen werde.		
	wel3	The technology ensures that I follow regulations, even if I didn't intend to.	Die Technologie sorgt dafür, dass ich mich an Vorschriften halte, auch wenn ich das nicht vorhatte.		
	wel4	To protect me, the technology is allowed to take control, even if it overrides my decisions.	Um mich zu schützen, darf die Technologie die Kontrolle übernehmen, auch wenn sie meine Entscheidungen außer Kraft setzt.		
Internal political efficacy	po1	I am good at understanding and assessing important policy issues.	Ich bin gut darin, wichtige politische Themen zu verstehen und einzuschätzen.	MV for CMB assessment	Groskurth et al. (2021)
	pol2	I have the confidence to play an active part in a discussion about political issues.	Ich habe das Selbstvertrauen, mich aktiv an einer Diskussion über politische Themen zu beteiligen.		
Metaverse knowledge		I know what the term "metaverse" means.	Ich weiß, was der Begriff "Metaverse" bedeutet.	MV for CMB assessment	ad hoc
		I am well acquainted with the subject of "metaverse."	Ich kenne mich mit dem Thema "Metaverse" gut aus.		
		I know how the metaverse works.	Ich weiß, wie das Metaverse funktioniert.		
Product autonomy	pat1	The technology determines itself how it conducts tasks.	Die Technologie bestimmt selbst, wie sie Aufgaben ausführt.	NV Study II.4	Rijsdijk et al. (2007)
	pat2	The technology makes decisions by itself.	Die Technologie trifft selbständig Entscheidungen.		
	pat3	The technology takes the initiative.	Die Technologie ergreift die Initiative.		
		The technology does things by itself.	Die Technologie macht die Dinge von selbst.		
Product intrusiveness	intr1	The technology is intrusive.	Die Technologie ist aufdringlich.	NV Study II.4	Mani and Chouk (2017)
	intr2	The technology is irritating.	Die Technologie ist lästig.		
	intr3	The technology is indiscreet.	Die Technologie ist indiskret.		
	intr4	I am not comfortable with the technology.	Ich fühle mich mit der Technologie nicht wohl.		
	intr5	The technology is disturbing.	Die Technologie ist störend.		
Perceived usefulness	PU1	Technology allows me to complete tasks faster.	Die Technologie ermöglicht es mir, Aufgaben schneller zu erledigen.	NV Study II.4	Davis (1989)
	PU2	Technology improves my performance.	Die Technologie verbessert meine Leistung.		
	PU3	Technology increases my effectiveness.	Die Technologie erhöht meine Effektivität.		
	PU4	The technology makes various tasks easier for me.	Die Technologie erleichtert mir diverse Aufgaben.		
	PU5	The technology is useful.	Die Technologie ist nützlich.		
Performance expectancy	PE1	I find the technology useful in my daily life.	Ich empfinde die Technologie in meinem Alltag als nützlich.	NV Study II.5	Venkatesh et al. (2012)
	PE2	Using the technology helps me accomplish things more quickly.	Die Nutzung der Technologie hilft mir dabei, Dinge schneller zu erreichen.		
	PE3	Using the technology increases my productivity.	Die Nutzung der Technologie erhöht meine Produktivität.		
Effort expectancy	EE1	Learning to use the technology is easy for me.	Die Nutzung der Technologie zu erlernen ist einfach für mich.	NV Study II.5	Venkatesh et al. (2012)
	EE2	My interaction with the technology is clear and understandable.	Meine Interaktion mit der Technologie ist klar und verständlich.		
	EE3	I find the technology easy to use.	Ich finde, die Technologie ist einfach zu nutzen.		
	EE4	It is easy for me to become skillful at using the technology.	Es ist einfach für mich, geübt in der Nutzung der Technologie zu werden.		

Note: NV = nomological validity; CMB = common method bias; MV = marker variable

Table 35: Means and standard deviations (Studies II.4 and II.5)

Study II.4										
Technologies in lottery		Auto-nomous car	AR glasses	Smart-phone	Smart home systems	Auto-correct function	Smart Coffee Mach.	Smart therm.	Smart speaker	Smart-watch
n		29	21	62	24	42	17	21	25	41
TP (overall)	M	4.12	3.21	3.19	3.05	3.01	2.98	2.96	2.86	2.64
	(SD)	(0.79)	(1.29)	(0.97)	(1.08)	(1.21)	(1.19)	(0.94)	(0.84)	(1.01)
limiting user freedom	M	3.69	3.01	3.45	2.96	3.06	2.72	2.86	2.97	2.77
	(SD)	(1.16)	(1.59)	(1.26)	(1.35)	(1.62)	(1.18)	(1.28)	(1.37)	(1.18)
lack of overruling pro-spects	M	3.88	2.95	3.08	2.51	2.45	2.93	2.66	2.73	2.25
	(SD)	(1.14)	(1.42)	(1.32)	(1.43)	(1.34)	(1.70)	(1.30)	(1.00)	(1.16)
welfare intention by technology	M	4.78	3.65	3.04	3.69	3.51	3.28	3.36	2.88	2.90
	(SD)	(0.78)	(1.24)	(1.17)	(1.07)	(1.20)	(1.33)	(1.09)	(1.02)	(1.09)
Study II.5										
Technologies in lottery		Auto-nomous car	AR glasses	Smart-phone	Smart home systems	Auto-correct function	Smart Coffee Mach.	Smart therm.	Smart speaker	Smart-watch
n		25	28	71	36	47	21	28	42	28
TP (overall)	M	3.99	3.36	3.14	2.93	2.86	3.31	3.28	3.32	3.09
	(SD)	(0.88)	(1.02)	(1.10)	(0.97)	(1.03)	(1.11)	(1.00)	(1.08)	(1.16)
limiting user freedom	M	3.82	3.38	3.21	2.88	3.05	2.87	3.02	3.40	2.97
	(SD)	(1.52)	(1.22)	(1.56)	(1.36)	(1.31)	(1.53)	(1.57)	(1.38)	(1.53)
lack of overruling pro-spects	M	3.51	3.11	3.35	2.63	2.27	3.19	2.73	3.15	2.89
	(SD)	(1.37)	(1.49)	(1.60)	(1.20)	(1.15)	(1.50)	(1.33)	(1.52)	(1.61)
welfare intention by technology	M	4.63	3.59	2.85	3.26	3.26	3.87	4.09	3.39	3.41
	(SD)	(1.18)	(1.19)	(1.13)	(1.11)	(1.35)	(1.40)	(1.14)	(1.16)	(1.36)

Note: SD = standard deviation; M = mean; mach.=machine; therm. = thermostat

Table 36: Correlations between marker variables and factors for CMV testing (Study II.5)

	Limiting user freedom	**Lack of overruling prospects**	**Welfare intention by technology**	**TP**
Internal political efficacy	-.038	-.108	.061	-.042
Metaverse knowledge	.068	-.017	.122*	.072

Note: Pearson Correlations; significance of correlations: * p<0.05; significant correlations marked in grey

Table 37: Common method bias test (Study II.5); model fit indices and model comparison for CFA models with both marker variables

Model	**X^2 (*df*)**	**CFI**	**RMSEA (90% CI)**	**LR of ΔX^2 (*df*)**	**Model comparison**
Internal political efficacy					
CFA with marker variable	257.467 (129)	.967	.055 (.045;.065)		
Baseline	265.563 (136)	.967	.054 (.044; .0)64		
Method-C (constrained)	265.563 (135)	.966	.055 (.045; .064)	0.000 (1); p= 1.000	vs. Baseline
Method-U (unconstrained)	249.276 (120)	.967	.058 (.047; .068)	16.287 (15); p = .363	vs. Method-C
Method-R (restricted)	249.349 (123)	.967	.056 (.046; .066)	0.073 (3), p = .995	vs. Method-U
Metaverse knowledge					
CFA with marker variable	288.777 (146)	.968	.055 (.046; .064)		
Baseline	297.032 (155)	.968	.053 (.044; .062)		
Method-C (constrained)	293.595 (154)	.969	.053 (.044; .062)	3.437, *df* = 1; p= .064	vs. Baseline
Method-U (unconstrained)	266.129 (139)	.971	.053 (.043;.063)	27.466, *df* = 15; p = .025	vs. Method-C
Method-R (restricted)	266.202 (142)	.972	.052 (.042; .061)	0.073, *df* = 3, p = .995	vs. Method-U

Note: CMB = common method bias; CFA = confirmatory factor analysis; CFI = comparative fit index; RMSEA = root mean square error of approx-imation; LR = likelihood ratio test

Table 38: CRediT statement paper II

Share of workload			
Martin Rochi	**Philipp A. Rauschnabel**	**Björn S. Ivens**	**Karl-Heinz Renner**
Conceptualization	Resources	Resources	Resources
Methodology	Conceptualization	Conceptualization	Conceptualization
Software	Methodology	Writing - Review & Editing	Writing - Review & Editing
Validation	Writing - Review & Editing	Supervision	Supervision
Formal analysis	Supervision		
Investigation	Funding acquisition		
Resources			
Data Curation			
Writing - Original Draft			
Writing - Review & Editing			
Visualization			
Supervision			
Project administration			
Funding acquisition			

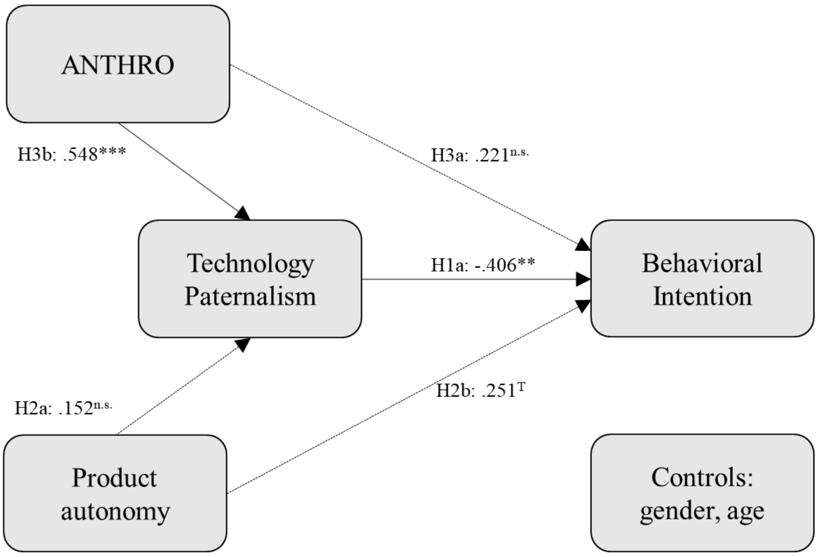
Note: Based on CRediT (Contributor Roles Taxonomy). A high-level taxonomy, that can be used to represent the roles typically played by contributors to research outputs. The roles describe each contributor's specific contribution to the scholarly output. For details, please see: https://credit.niso.org/

Appendix – Paper III – Chapter 4

Table 39: List of all items used (Paper III)

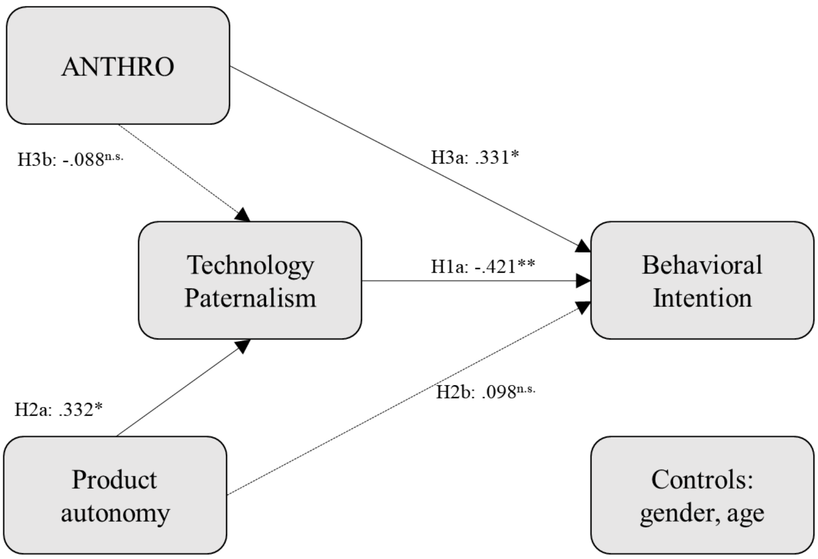
Scale	Code	Items (English)	Study	Source
Technology paternalism Note: "The technology" serves as a placeholder for the technology under consideration.	auto1	*The technology* restricts my freedom.	Study III.1 Study III.2 Study III.3	Rochi et al. (2024)
	auto2	*The technology* makes me lose freedom of choice.		
	auto3	*The technology* overrides my desires.		
	auto4	*The technology* disregards my wishes.		
	auto5	*The technology* decides against my will.		
	auto6	I feel like I'm externally controlled by *the technology*.		
	auto7	*The technology* is authoritarian.		
	over1	The final decision is up to *the technology*, even if I don't want it to be.		
	over2	I can't overrule the decisions of *the technology*.		
	over3	I can't get around the choices of *the technology*.		
	over4	*The technology* requires that I submit.		
	over5	*The technology* forces me to accept its decisions.		
	wel1	*The technology* ensures that I follow rules.		
	wel2	*The technology* wants the best for me, even if that means overruling me.		
	wel3	*The technology* ensures that I follow regulations, even if I didn't intend to.		
	wel4	To protect me, *the technology* is allowed to take control, even if it over-rides my decisions.		
Product autonomy Note: "The technology" serves as a placeholder for the technology under consideration.	pat1	*The technology* determines itself how it conducts tasks.	Study III.1 Study III.2 Study III.3	Rijsdijk et al. (2007)
	pat2	*The technology* makes decisions by itself.		
	pat3	*The technology* takes the initiative.		
	pat4	*The technology* does things by itself.		
Anthropomorphism Note: "The technology" serves as a placeholder for the technology under consideration.	an1	*The technology* looks almost like a human.	Study III.1 Study III.2 Study III.3	Adapted from Epley et al. (2007) and S. Kim and McGill (2011)
	an2	*The technology* almost looks as if it has a mind of its own.		
	an3	It almost seems as if *the technology* has its own intentions.		
	an4	It seems as if *the technology* is emotional in a way.		
Behavioral Intention Note: "The technology" serves as a placeholder for the technology under consideration.	bi1	If I had a *technology* like this in my household, I would use it as often as possible	Study III.1 Study III.3	Adapted from Venkatesh et al. (2003)
	bi2	If I had a *technology* like this in my household, I would use it very inten-sively.		
	bi3	If there was a technology like this in my household, I would be happy to use it.		
Technology resistance	res1	If there were such a robot vacuum cleaner in my household, I would de-liberately not use it.	Study III.2 Study III.3	Ad-hoc
	res2	If there was a robot vacuum cleaner like this in my household, I'd reject it out of hand.		
	res3	If there was such a robot vacuum cleaner in my household, I would refuse to use it.		
	res4	If there was such a robot vacuum cleaner in my household, I would be totally "against" it.		
Domain-specific Innovativeness	dsi1	I'm the first person in my circle of friends to buy new smart products when they come onto the market.	Study III.2	M. Li et al. (2023)
	dsi2	I like to buy new smart products earlier than others do.		
	dsi3	When a new smart product comes onto the market, I like to buy it.		
	dsi4	I am the first to know the name of a new smart product.		
Product involvement	pinv1	The robot vacuum cleaner is very important to me personally.	Study III:2	Adapted from Bauer et al. (2006)
	pinv2	I am interested in the robot vacuum cleaner.		
	pinv3	My general interest in robot vacuum cleaners is high.		
	pinv4	A robot vacuum cleaner is very important to me.		
Metaphoric thinking Completion instructions: Please indicate which variant cor-responds more closely to your own use of language if you were talking about the (fictitious) well-known person called "Chrissi".	meta1	Chrissi's place is a mess! – Chrissi's place looks like it's been hit by a bomb!	Study III.2	Adapted from Fetterman et al.
	meta2	Chrissi doesn't give a clear answer. – Chrissi just beats around the bush.		
	meta3	Chrissi would like to pay you a compliment. - Chrissi wants to butter you up.		
	meta4	Chrissi is naive. - Chrissi is wearing rose-colored glasses.		
	meta5	Chrissi and you are a good match. - Chrissi and you, that fits like a glove.		

Figure 13: Results of Study III.1 (only smart vacuum cleaner); dotted lines represent not significant paths)



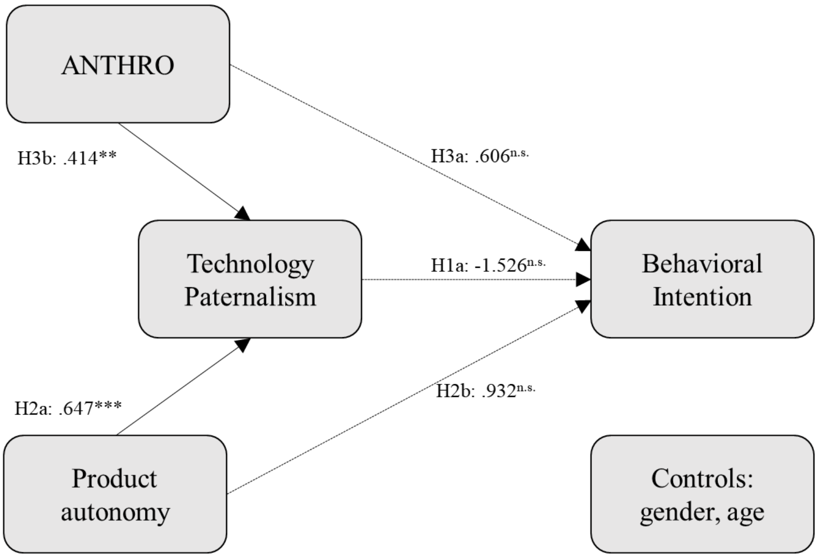
H2d: product autonomy → technology paternalism → behavioral intention; no mediation
H3d: anthropomorphism → technology paternalism → behavioral intention; full mediation (indirect effect b = -.223*)
Controls: no significant relationships

Figure 14: Results of Study III.1 (only smart speaker); dotted lines represent not significant paths)



H2d: product autonomy → technology paternalism → behavioral intention; no mediation
H3d: anthropomorphism → technology paternalism → behavioral intention; no mediation
Controls: no significant relationships

Figure 15: Results of Study III.1 (only smart watch); dotted lines represent not significant paths)



H2d: product autonomy → technology paternalism → behavioral intention; no mediation
H3d: anthropomorphism → technology paternalism → behavioral intention; no mediation
Controls: no significant relationships

Figure 16: Survey optical stimuli (Study III.1) (in German)

Stimuli – smartwatch

Nun werden wir etwas detaillierter. Die nächsten Fragen drehen sich alle um eine bestimmte Kategorie von smarten Produkten.

Kategorie: SMARTWATCHES

Eine Smartwatch ist eine elektronische Armbanduhr die über zusätzliche Sensoren, Aktuatoren (z. B. Vibrationsmotor) sowie Computerfunktionalitäten und -konnektivitäten verfügt. Wesentliches Merkmal von Smartwatches ist, dass sich neben der Uhrzeit weitere Informationen darstellen lassen und der Anwender zusätzliche Funktionen über Programme („Apps") individuell aufrüsten kann.

Nutzungsbeispiel: Durch die Sensorik ist das Erkennen von Anomalien möglich, was beispielsweise die Anwendung für ältere Menschen (Sturzerkennung, Assistenz, Epilepsie), bei gefährdeten Arbeitsplätzen oder medizinische Anwendungen erlaubt. Auch für die Erkennung von Herzrhythmusstörungen – etwa Vorhofflimmern – werden Smartwatches eingesetzt. Seit 2019 gibt es auch ein Modell, welches den Blutdruck messen kann.

Beispiele für Smartwatches:

Huawei Watch3 Pro | Samsung Galaxy Watch 5 | Apple Watch Ultra

Besitzen Sie eine Smartwatch der vorgestellten Art oder ein ähnliches Produkt?

- ◯ JA
- ◯ NEIN

1.3.1 Erläuterung Saugroboter

Stimuli – smart vacuum cleaner

Nun werden wir etwas detaillierter. Die nächsten Fragen drehen sich alle um eine Kategorie von smarten Produkten.

Kategorie: smarte Staubsauger

Smarte Staubsauger sind kleine, wendige Maschinen, die dem Nutzer Arbeit abnehmen können. Ein smarter Staubsauger ist ein autonomer Roboter, der über ein Bodenreinigungssystem verfügt, das mit Sensoren und Roboterantrieben mit programmierbaren Steuerungen und Reinigungsroutinen kombiniert ist. Einige Modelle verwenden rotierende Bürsten, um enge Ecken zu erreichen, und einige verfügen neben der Saugfunktion über eine Reihe von Reinigungsfunktionen (Wischen, UV-Sterilisation usw.). Aktuelle Modelle nutzen künstliche Intelligenz und Deep Learning für eine bessere Kartierung, Objekterkennung und ereignisbasierte Reinigung.

Beispiele für smarte Staubsauger:

Dreame Bot L10 Pro

Ecovacs Deebot X1 Omni

Roborock S7 MaxV Ultra

Besitzen Sie einen smarten Saugroboter der vorgestellten Art oder ein ähnliches Produkt?

- ○ JA
- ○ NEIN

1.4.1 Erläuterung smart speaker

Stimuli – smart speaker

Nun werden wir etwas detaillierter. Die nächsten Fragen drehen sich alle um eine Kategorie von smarten Produkten.

Kategorie: Smart Speaker

Ein Smart Speaker ist ein mit dem Internet verbundener Lautsprecher, der Musik oder Sprache drahtlos überträgt und per eingriffsfreier Sprachsteuerung und Spracherkennung die Funktionen eines intelligenten Persönlichen Assistenten (IPA) integriert. Die Geräte verfügen meist über leistungsfähige Hardware, die die Sprachbefehle mittels mehrerer Mikrofone aufzeichnet. Damit werden Audioaufnahmen erzeugt, die auf den verarbeitenden Servern wirkungsvoll verarbeitet werden können.

Beispiele für Smart Speaker:

Amazon Echo Studio

Sonos Era 300

Apple Homepod 2

Besitzen Sie einen Smart Speaker der vorgestellten Art oder ein ähnliches Produkt?

- ◯ JA
- ◯ NEIN

1.5.1 Erläuterung weiteres vorgehen

Die nächsten Fragen drehen sich alle um das eben vorgestellte Produkt "#ListeProdukte#".

WICHTIG:

Die folgenden Fragen im Kontext "#ListeProdukte#" können etwas abstrakt klingen. Sie könnten sich fragen "was soll das bedeuten?".
Wir bitten Sie, sich hiervon nicht abschrecken zu lassen. Versuchen Sie dennoch die Fragen so ehrlich wie möglich zu beantworten.
Wenn Sie keine(n) #ListeProdukte# besitzen, versuchen Sie bitte, sich in eine Interaktion mit diesem Produkt hineinzuversetzen.

1.5.2.1 TPS (16 items)

Figure 17: Survey optical stimuli (Study III.2) (in German; (commercially available smart vacuum cleaner)

Stimuli – Roborock S8 Pro Ultra – commercially available on market

Wir dürfen vorstellen:
Den smarten Staubsauger-Roboter Roborock S8 Pro Ultra für nur 1.499 Euro.

Bitte schauen Sie sich die hier vorhandenen Informationen zu dem Staubsauger-Roboter genau an. Die folgenden Fragen beziehen sich auf dieses Produkt. Der "Weiter-Button" wird in 30 Sekunden angezeigt.

Figure 18: Survey optical stimuli (Studies III.2 and III.3) (in German)

Stimuli – high anthropomorphism / high paternalism

Hi! Ich bin JESSI! Deine Haushaltshelferin der nächsten Generation!

- **Handeln**: Ich sauge und wische selbstständig, ohne dass du es mir befehlen musst.
- **Kommunizieren**: Ich kann via Sprachausgabe immer mit dir kommunizieren, um dein Reinigungserlebnis weiter zu verbessern.
- **Lernen**: Ich lerne selbstständig die Wohnung kennen, ohne deine Zustimmung zu benötigen.
- **Antizipieren**: Ich entwickle selbständig ein Gespür für dich als Nutzer und weiß, wann welcher Raum gereinigt werden muss, ohne deine Kommandos abzuwarten.

Highlights:

- Wenn Du mit dreckigen Schuhen über den Boden läufst, **mahnt** dich JESSI, diese auszuziehen. So machst Du weniger Dreck in der Wohnung.
- Für höchste Performance trifft JESSI **selbstständig** und ohne dir Bescheid zu geben Entscheidungen. Dadurch sind optimale Reiningungspläne und Abläufe sichergestellt.
- Über die JESSI-App kannst du **geringfügige Veränderungen** vornehmen. JESSI´s Funktionen sind **automatisiert** und **voreingestellt**, damit sie immer volle Leistung bringen kann!
- JESSI meldet dir täglich ihre Leistungsdaten und **gibt selbstständig Tipps** zur Bodenreinigung und zur allgemeinen Sauberkeit im Haushalt. Und das zusätzlich zu den Stunden an Hausarbeit, welche sie dir abnimmt!

Der "WEITER" Button erscheint in 30 Sekunden.

Stimuli – high anthropomorphism / low paternalism

Hi! Ich bin JESSI! Deine Haushaltshelferin der nächsten Generation!

- **Handeln**: Ich sauge und wische selbstständig.
- **Kommunizieren**: Ich kann (wenn gewünscht) via Sprachausgabe mit dir kommunizieren, um dein Reinigungserlebnis weiter zu verbessern.
- **Lernen**: Ich kann die Wohnung selbstständig kennenlernen.
- **Antizipieren**: Ich entwickle ein Gespür für dich als Nutzer und lerne, wann welcher Raum gereinigt werden kann.

Highlights:

- Wenn du es **wünschst**, kann ich dir mitteilen, wenn deine Schuhe dreckig sind, damit weniger Dreck in die Wohnung gelangt.
- Für höchste Anpassbarkeit an Deine Bedürfnisse führe ich lediglich **Grundfunktionen automatisch** aus.
- Selbstverständlich kannst Du über die JESSI-App **alle Einstellungen** ändern. So bist du der Herr im Haus und hast die volle Kontrolle.
- Wenn du es **wünscht**, melde ich dir meine Leistungsdaten im von Dir gewünschten Turnus.

1.4.1.1 Wie lautet der Name?

Stimuli – low anthropomorphism / high paternalism

Das ist der neue IES23i! Der Haushaltshelfer der nächsten Generation!

- Handeln: Der IES23i saugt und wischt selbstständig, ohne dass du es ihm befehlen musst.
- Kommunizieren: Der IES23i kann via Sprachausgabe immer mit dir kommunizieren, um dein Reinigungserlebnis weiter zu verbessern.
- Lernen: Der IES23i lernt selbstständig die Wohnung kennen, ohne deine Zustimmung zu benötigen.
- Antizipieren: Der IES23i speichert Deine Nutzerdaten und weiß, wann welcher Raum gereinigt werden muss, ohne deine Kommandos abzuwarten.

Highlights:

- Wenn Du mit dreckigen Schuhen über den Boden läufst, mahnt dich der IES23i, diese auszuziehen. So machst Du weniger Dreck in der Wohnung.
- Für höchste Performance trifft der IES23i selbstständig und ohne dir Bescheid zu geben Entscheidungen. Dadurch sind optimale Reiningungspläne und Abläufe sichergestellt.
- Über die IES-App kannst du geringfügige Veränderungen vornehmen. Die meisten Funktionen sind voreingestellt, damit der IES23i immer volle Leistung bringen kann.
- Der IES23i meldet dir täglich Leistungsdaten und gibt selbstständig Tipps zur Bodenreinigung und zur allgemeinen Sauberkeit im Haushalt. Und das zusätzlich zu den Stunden an Hausarbeit, welche er dir abnimmt.

Stimuli – low anthropomorphism / low paternalism

Das ist der neue IES23i! Der Haushaltshelfer der nächsten Generation!

- **Handeln**: Der IES23i saugt und wischt selbstständig.
- **Kommunizieren**: Der IES23i kann (wenn gewünscht) via Sprachausgabe mit dir kommunizieren, um dein Reinigungserlebnis weiter zu verbessern.
- **Lernen**: Der IES23i kann die Wohnung selbstständig kennenlernen.
- **Antizipieren**: Der IES23i speichert deine Nutzerdaten und lernt, wann welcher Raum gereinigt werden kann.

Highlights:

- Wenn du es **wünschst**, kann der IES23i dir mitteilen, wenn deine Schuhe dreckig sind, damit weniger Dreck in die Wohnung gelangt.
- Für **höchste Anpassbarkeit** an deine Bedürfnisse führt der IES23i lediglich **Grundfunktionen** selbständig aus.
- Du kannst über die IES-App **ALLE** Einstellungen ändern. So bist du der Herr im Haus und hast die volle Kontrolle.
- Wenn du es **wünscht**, meldet dir der IES23i seine Leistungsdaten im von dir gewünschten Turnus.

1.6.1.1 Wie lautet der Name?

Statement regarding editing services

Parts of this dissertation have already been published as articles in journals. In the course of the pre-publication work for these articles, editing services were used to improve the writing style, as the author is a non-native English speaker. The provider of this editing service was scribendi.com. Some paragraphs of this dissertation were edited with the help of GPT and DeepL to make the texts more precise. Neither Scribendi, GPT nor DeepL were involved in the content creation of the texts and did not contribute content to the dissertation beyond proofreading or editing services.

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