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Research article

ChatGPT usage in everyday life: A motivation-theoretic mixed-methods study

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ABSTRACT

GenAI-driven technologies such as ChatGPT influence activities in all areas of life and are used in private and work contexts. This study uses an individual-centered perspective to explain what motivates users to use ChatGPT continuously. We propose that four motivational factors and two technology characteristics together lead to continuance intention among individual ChatGPT users. Therefore, we use a mixed-methods design to combine findings from a quantitative survey study and a qualitative interview study. In Study 1, we follow a configurational approach to analyze multi-wave data from 279 participants with fsQCA. We identify five configurations that lead to high continuance intention and show that perceived ease of use and perceived novelty are necessary for this outcome. Interestingly, the observed factors together cannot explain low continuance intention. In Study 2, we complement these findings with insights based on 15 semi-structured interviews. We illustrate the configurations by identifying 27 individual use cases in the private and work contexts as well as additional factors that facilitate and hinder individual ChatGPT continuance intention. We draw meta-inferences by combining findings of both studies to develop five propositions. Based on that, we contribute a motivational, individual perspective on GenAI continuance intention, present practical implications as well as valuable future research opportunities.

1. Introduction

Generative artificial intelligence (GenAI) assists users in most areas of their daily lives. For example, users benefit from language translation (Kenny, 2022) and writing assistance (Dale & Viethen, 2021) in both private and work contexts. GenAI, as applied in ChatGPT, powers helpful applications such as chatbots, already half of US mobile users use voice search daily (Haan & Watts, 2023), and other application areas continue to emerge at breakneck speed (McKinsey & Company, 2022). Consumer applications rely increasingly on GenAI, and GenAI is expected to have significant and continued relevance for all industrial and life sectors, from agriculture to education, finance, and telecommunication (Webb & Chockalingam, 2023). This exceptional development raises the question of what factors motivate individual users to continue using GenAI applications such as ChatGPT in private and work contexts.

In order to understand what motivates users, we follow a motivational-theoretic approach and align with research that typically differs between intrinsic and extrinsic motivational factors (Vallerand, 1997). Intrinsic factors are those that are satisfied by the mere performance of an activity, and extrinsic factors lie outside the performed activity and the performer, in the context of IS usually referring to the user's perceived usefulness. In this study, we focus on intrinsic and extrinsic motivational factors to develop theory how these together influence continuance intention of ChatGPT, as a specific example of GenAI. We further contextualize our theoretical understanding by considering two technology characteristics that are relevant when studying use behavior of new IS (Cenfetelli, 2004; Wells, Campbell, Valacich, & Featherman, 2010): perceived novelty and perceived ease of use. Following recent arguments of equifinality revealing that behavior is driven by a polyvalent interplay of factors (Maier, Laumer, Joseph, Mattke, & Weitzel, 2021), we theorize that combinations of these motivational factors and technology characteristics together lead to continuance intention. This means that individuals assess that multiple, different factors in configurations lead to continuance intention. We therefore aim to show that, for example, some individuals ground their continuance in intrinsic motivation together with perceived novelty, and other individuals may ground their continuance in extrinsic motivation in combination with perceived ease of use. Thus, we aim to

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answer the following research question:

> **Which configurations of motivational factors and technology characteristics lead to high and low continuance intention among ChatGPT users?**

To answer this research question, we set up a two-part mixed-methods study. In the first quantitative study, we use well-established arguments from motivation theory and collect multi-wave data from 279 participants who have used ChatGPT. We then draw on fuzzy-set qualitative comparative analysis (fsQCA) to unfold the configurations. In the subsequent qualitative study, we conduct 15 semi-structured interviews to illustrate these configurations with actual use cases and enrich them with further facilitating and hindering factors. Taken together, we extend the literature with a motivational and individual perspective on GenAI usage behavior and also account for its causal complexity; thus, we contribute to continuance intention research by highlighting the polyvalent role of motivational factors in the context of ChatGPT usage. Based on meta-inferences of both studies, we develop propositions, formulate practical implications and suggest valuable future research opportunities.

The remainder of this paper is organized as follows: Section 2 outlines relevant research on ChatGPT, continuance intention, motivational factors, and technology characteristics in the context of IS use. Section 3 describes the research design, and Sections 4 and 5 are dedicated to our two studies, including methodology and results. Section 6 discusses theoretical and practical implications, limitations of the study, and future research prospects, and a conclusion is provided in Section 7.

2. Literature review

We summarize the significant tenets of research on ChatGPT and explain the impact of continuance intention on usage behavior and its connection to motivation theory.

2.1. Artificial intelligence and ChatGPT

In a broad sense, artificial intelligence (AI) refers to systems that algorithmically perform certain tasks that simulate components of human intelligence (Melville, Robert, & Xiao, 2022). AI is considered by many to be an essential factor of digital transformation, offering immense processing power for diverse data types and large quantities (Markus & Rowe, 2023). While the strategic and organizational view on AI has been extensively addressed by recent research – e.g., marketing (Kshetri, Dwivedi, Davenport, & Panteli, 2023) and organizational IS adoption (Uren & Edwards, 2023) – we find that there is a need for further investigation of AI use at the individual level, for example how the factors leading to individual AI use differ between the private and work contexts.

One AI application of broader public interest is ChatGPT. It is an example of GenAI, meaning that it cannot only process data but also generate it by recreating patterns of analyzed training samples (Jovanović & Campbell, 2022). Based on natural language processing (NLP) technology, ChatGPT is a large language model (LLM) with a chatbot-like user interface capable of text-to-text tasks in response to natural language. Despite its exemplarity due to its high number of users (Armstrong, 2023), contributions in IS research using ChatGPT as an appropriate example of GenAI applications are still limited. So far, studies focus on evaluations of GenAI-based algorithms (Nishant, Schneckenberg, & Ravishankar, 2023), ethics in GenAI use (Stahl & Eke, 2024), or the potential in adoption of GenAI applications (Dwivedi, Pandey, Currie, & Micu, 2024), whereby research involving the actual and particularly individual use of GenAI applications such as ChatGPT is scant. Against that background, our focus is to study what leads to high and low continuance intentions for GenAI as exemplified by ChatGPT.

2.2. Continuance behavior, motivational factors, and technology characteristics

IS usage is one of the most established research directions, which deals with various usage behaviors (Maier, Laumer, Weinert, & Weitzel, 2015; Tamilmani, Rana, Wamba, & Dwivedi, 2021). Since many individuals have already started using ChatGPT and we are interested in understanding the role of motivation in continued use, we consider continuance intention as the outcome of interest. Continuance intention is the willingness to continue using a currently used IS (Bhattacherjee, 2001), and in our study, we consider it as a proxy for actual continued use behavior (Jeyaraj, Dwivedi, & Venkatesh, 2023).

Previous research on IS continuance intention has relied on theoretical models assuming that motivational factors influence continuance intention without explicitly labeling them as such (Tamilmani et al., 2021). The consideration of factors such as enjoyment and usefulness is in line with the distinction between intrinsic and extrinsic motivational factors that lead to behavior; in this context, intrinsic means derived from performing an activity itself – e.g., enjoyment – and extrinsic means caused by the reinforcing value of outcomes – e.g., usefulness – (Vallerand, 1997). Notably, those motivational factors moderate each other, e.g., extrinsic motivation, such as payment, can lead to a decrease in intrinsic motivation for an activity (Deci, 1971).

We build on and extend this knowledge by highlighting the importance of considering both types of motivational factors, particularly by accounting for the complexity of intrinsic motivation. Indicators of enjoyment are often considered sufficient to assess intrinsic motivation, but they under-conceptualize this motivational component (Li, Hsieh, & Rai, 2013). Focusing on the hedonic aspect of IS use, perceived enjoyment conveys the pleasure-oriented meaning of intrinsic motivation in a more general sense (van der Heijden, 2004). The concept of rich intrinsic motivation (RIM) instead distinguishes three components of intrinsic motivation (Li et al., 2013). Here, intrinsic motivation to accomplish ($InM_{accomplish}$), to know (InM_{know}), and to experience stimulation ($InM_{stimulation}$) account for the complexity of intrinsic motivation and allow for an evaluation of their interaction in explaining usage behavior. Motivational factors are addressed in the research of continuance intention (Yan, Filieri, & Gorton, 2021), but not with the sufficiently elaborated distinction between them that RIM provides.

To account for the second form of motivational factor, extrinsic motivation, we draw on perceived usefulness (ExM_{PU}). ExM_{PU} is a measure of the extent to which a particular IS enhances the user's performance (Venkatesh, Morris, Davis, & Davis, 2003), and it is an essential factor for IS use. It is reasonable to categorize ExM_{PU} as a technology attribute, but from a utilitarian perspective, the clear focus on outcome values also qualifies ExM_{PU} as a common example of extrinsic motivation (Davis, Bagozzi, & Warshaw, 1992). The use of an IS to save time, money, or any form of work capacity through usefulness is done because of the reinforcing value of the outcomes and is therefore extrinsically motivated. In the context of GenAI, ExM_{PU} is discussed in research areas such as IS adoption in accounting (Damerji & Salimi, 2021) or interaction with game avatars (Butt, Ahmad, Goraya, Akram, & Shafique, 2021).

In addition to these motivational factors, we argue that there is a need to consider contextually relevant factors, as motivational influences on behavior vary depending on the context (Vallerand, 1997). In the case of GenAI, as exemplified by ChatGPT, we consider the establishment of innovative and disruptive technology as our specific study context (Hong, Chan, Thong, Chasalow, & Dhillon, 2014). Therefore, we draw on two related perceptions of technology characteristics: perceived ease of use (TeC_{PEOU}) and perceived novelty (TeC_{NVL}). First, research needs to consider whether an IS has a high TeC_{PEOU}, as this is critical to whether a technology is adopted and whether users are willing to continue using it (Lowry, Gaskin, & Moody, 2015) – crucial for a technology that did not previously exist in this form. TeC_{PEOU} is an established factor influencing usage behavior and refers to the extent to which users believe that using a particular IS is effortless (Venkatesh et al., 2003). Second, users evaluate IS newness subjectively, which in turn influences usage behavior (Mani & Chouk, 2017) – this is particularly relevant for innovative IS, such as ChatGPT, which is distinguished from others by its newness. The subjective evaluation of newness is reflected in TeC_{NVL} as a significant antecedent of behavioral intention (Wells et al., 2010). While TeC_{NVL} is evidently not a motivational factor, previous research has interpreted TeC_{PEOU} as an intrinsic motivational factor due to the inherent ease-joy nexus (van der Heijden, 2004). Since equating joy with intrinsic motivation is not comprehensive enough, and TeC_{PEOU} clearly focuses on the perception of IS characteristics, we consider it a technology-oriented factor. Therefore, the study draws on TeC_{PEOU} and TeC_{NVL} as technology characteristics, considering that ChatGPT is still a relatively new technology that users must become familiar with.

2.3. Research framework

Our research model uses three different groups of factors: intrinsic motivational factors, extrinsic motivational factors, and technology characteristics. We consider three intrinsic motivational factors: $InM_{accomplish}$, InM_{know}, and $InM_{stimulation}$. We complement them with the extrinsic motivational factor ExM_{PU}. We also include the two technology characteristics TeC_{PEOU}, and TeC_{NVL}. Motivational factors and technology characteristics can have a linear and unidirectional influence on continuance intention (Lowry et al., 2015). We advance this knowledge by arguing that their complex interactions let users experience them holistically as configurations that together lead to high or low continuance intention. The rationale is that usage behavior is driven by a polyvalent interplay of motivational factors and technology characteristics (Hong et al., 2014; Vallerand, 1997). This means it cannot be explained in a monocausal, purely symmetrical, and unidirectional manner that neglects the complex influences of multiple interacting causal factors.

We argue that various motivational factors drive our individual behavior at any given time (Vallerand, 1997). We further expect them to interact, given the potential attenuation of intrinsic motivation in the presence of extrinsic motivation (Deci, 1971). In this sense, we expect to see further mutual influence effects of motivational factors, including between different intrinsic motivational factors. For example, a user who is highly motivated by knowledge acquisition and demotivated by stimulation may be more likely to engage in instructive activities depending on the level of excitement they experience, and vice versa. Theoretically, this will show interdependencies in terms of complementarity, contingency, or substitution (Pflügner, Maier, Thatcher, Mattke, & Weitzel, 2024). Furthermore, the context shapes perception as well as evaluation, thus adding another level of complexity to explanations of behavior (Hong et al., 2014). In the context of establishing innovation, technology that is characterized as novel may satisfy both needs – to acquire knowledge through learning potential and to experience stimulation through unknown sensation – but novelty may act here as a necessary enabler for the two motivational factors to exert their influence. This, in turn, influences the possible mutually influential relationship of the motivational factors.

To assess how complex mutual influences of motivational factors – intrinsic and extrinsic – and technology characteristics – capturing perceptions of users' familiarity with novel IS – lead to high or low continuance intention, we posit a model of individual users' motivations and perceptions of technology characteristics (see Fig. 1). We use fsQCA because it is suitable for explaining behavior and has already been successfully used to study continuance intention (Mattke, Maier, Weitzel, & Thatcher, 2021; Pappas, Papavlasopoulou, Mikalef, & Giannakos, 2020). Furthermore, it is particularly suited for accounting for causal complexity by identifying configurations retroductively, i.e., formulating explanations by inferring concomitant factors of a given outcome from multifactorial data.

3. Research design: mixed-methods approach

Following a mixed-methods approach (Venkatesh, Brown, & Bala, 2013), we conducted two studies to investigate which configurations of motivational factors and technology characteristics lead to high and low continuance intention among ChatGPT users; see Fig. 2. First, to find the necessary conditions and sufficient configurations of these factors, we performed a fsQCA on the quantitative basis of survey data. Second, we conducted an interview study to identify use cases in private and work-related contexts that shed light on the results and to find additional relevant factors. Mixed-methods approaches combining interviews with quantitative analyses are common in IS research (Deodhar, Babar, & Burtch, 2022), and qualitative analyses, used not as a basis for quantitative research but as a tool to provide an additional explanatory perspective, have proven beneficial (Addas & Pinsonneault, 2015). This allows us to make meta-inferences that go beyond simply reporting the results of two independent studies.

4. Study 1: Quantitative survey study

This study aims to identify configurations of motivational factors and technology characteristics that lead to high and low continuance intention among ChatGPT users. Therefore, we set up a quantitative survey and conducted a fsQCA.

4.1. Method

In the following, we describe the data collection process, the measures, and the procedures used for data analysis.

4.1.1. Data collection and sample

As recommended in previous IS research to use multi-wave data collection (Maier, Thatcher, Grover, & Dwivedi, 2023), we set up a

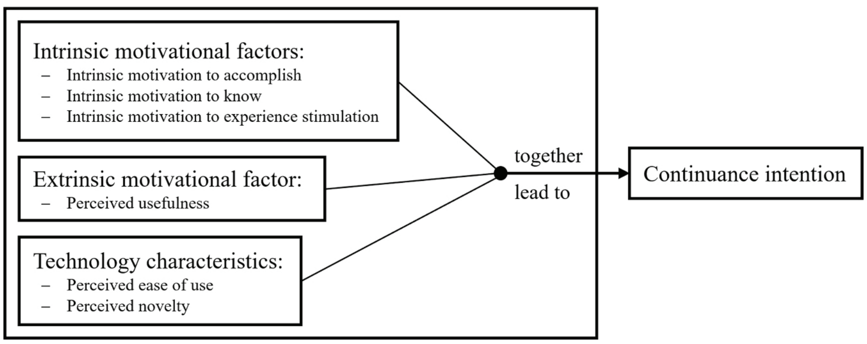

Fig. 1. Research model.

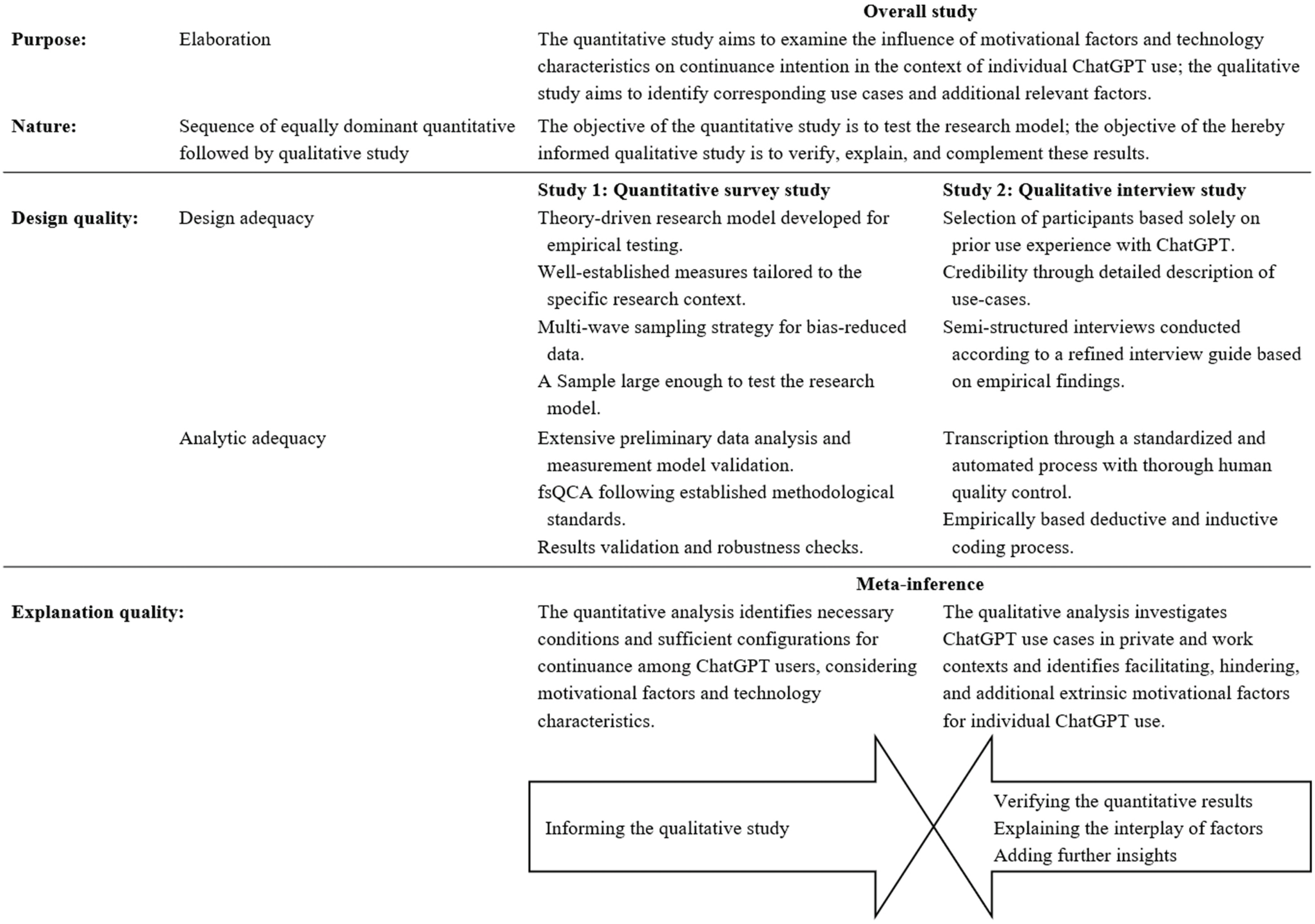

Fig. 2. Mixed-methods study design (scheme adapted from Maier, Laumer, Thatcher, Wirth, & Weitzel, 2022).

three-part online survey to collect data from ChatGPT users. We used Prolific, an on-demand, self-service data collection platform, to recruit these participants. It provides proven high data quality regarding attention, response content, instructional acceptance, and accuracy (Douglas, Ewell, & Brauer, 2023), and it is suitable for multistage surveys (Palan & Schitter, 2018). Following established methodological guidelines for setting up a survey on online crowdsourcing platforms, we ensured the quality of our data (Lowry, D'Arcy, Hammer, & Moody, 2016). We have limited our sample to participants located in the US and ChatGPT users, included reverse questioning as an attention control, and paid £ 12.44, almost twice the US minimum wage. In total, the data collection process took two weeks and started about half a year after the public release of ChatGPT.

We conducted the study in three waves. In the first wave, 1000 participants took the screening test created with Prolific's proprietary survey tool. It consisted of five questions with binary yes-or-no options, four of which were designed to distract from the question of interest, whether they had used ChatGPT at least once; exemplary items are "Have you ever attended a classical music concert?" or "Have you ever gone jogging?". 642 participants who chose the positive option regarding previous use of ChatGPT were invited to continue participating. In the second wave, 400 participants accepted this invitation. They completed an online survey created with LimeSurvey, which is suitable for more complex questionnaires than the screening test created with Prolific. This survey comprised items measuring the independent variables, half of the demographic information, and a control variable for common method bias. In the third wave, 366 participants from the second wave decided to continue their participation. They completed another survey measuring the dependent variable with the other half of the demographics and a second control variable for common method bias.

We excluded very fast and inaccurate respondents regarding arbitrary or patterned response behavior as part of the data preparation. Consistent with previous behavioral research (Buchanan & Scofield, 2018), we assessed participants who responded faster than two standard deviations below the sample mean response speed (assuming a normal distribution) as unlikely to respond conscientiously. To account for them, we dropped datasets of participants who exceeded this threshold in one or both parts of the survey. Similarly, participants with a standard deviation of less than one across all responses and a difference of more than four points in an inverted question were also excluded, resulting in a sample of 279 datasets.

We then checked the ratio of conditions to observations, which should be less than .20 to avoid the identification of sufficient random configurations (Marx & Dusa, 2011). The present sample meets this requirement with a ratio of .02 (six conditions to 279 observations); thus, fsQCA is viable. The demographic information of the sample is presented in Table 1.

4.1.2. Measurement items

We developed the present survey on measures established in previous research; a complete overview of all survey items is provided in the Appendix (Table 17). In our survey, we included $InM_{accomplish}$ with four items, InM_{know} as well as $InM_{stimulation}$ with three items (Li et al., 2013), and ExM_{PU} with six items (Hess, McNab, & Basoglu, 2014). We measured continuance intention with three items, one of which was reversed (Bhattacherjee, 2001). To account for ChatGPT being a relatively new technology, we evaluated TeC_{PEOU} with six items (Hess et al.,

Table 1
Demographics of 279 survey participants.

Age (in percent) Mean: 37.30, SD: 12.26, Range: 19–75		Gender (in percent)		Nationality (in percent)		Education (in percent)		Job in IT (in percent)		Other AI applications in use (in percent)	
< 25	13.98	Female	42.65	USA	84.59	E1	0.36	No	74.19	Dall-E	33.69
25–34	36.56	Male	56.99	NGA	1.79	E2	0.00	Yes	25.81	YouChat	24.73
35–44	26.52	Nonbinary	0.36	UK	1.79	E3	26.88			DeepL	8.96
45–54	11.11			ROK	1.08	E4	8.60			Simplified	5.73
55–64	7.89			Others:	10.75	E5	48.03			Jasper Chat	5.38
> 64	3.94					E6	12.90			Bing Chat	2.87
						E7	3.23			Google Bard / Gemini	2.87
										Midjourney	1.79

Note: NGA = the Federal Republic of Nigeria, ROK = the Republic of Korea; E1 = Elementary or primary education, E2 = Lower secondary education (approx. 5 to 10 years), E3 = Higher secondary education (11 to 13 years), E4 = Non-academic professional degree, E5 = Bachelor’s degree or equivalent level, E6 = Master’s degree or equivalent level, E7 = Doctoral degree or equivalent level.

2014) and TeC_{NVL} with three items (Wells et al., 2010). We adapted all measures to fit the context of ChatGPT; instruments developed in work-related research were adjusted to suit everyday life scenarios. For example, “Using the BIS (Business information system) in my job enables me to accomplish tasks more quickly.” was replaced by “Using ChatGPT enables me to accomplish tasks more quickly.” (first item of ExM_{PU}). All items were scored on a seven-point Likert scale from “strongly disagree” (1) to “strongly agree” (7). To account for common method bias, we chose a temporal separation (one week) of the dependent and independent variables (Jordan & Troth, 2020): we included the measures corresponding to the configurational variables (motivational factors and technology characteristics) in the first questionnaire, and the measures corresponding to the outcome variable (continuance intention) thus in the second part.

4.1.3. Data analysis using fsQCA

Configurational approaches such as fsQCA employ asymmetrical empirical modeling techniques beyond reasoning based on single correlative relationships (Gandhi & Kar, 2024). In the logic of this analysis, independent variables are called conditions, and dependent variables are referred to as outcomes. The fsQCA is capable of identifying necessary conditions – conditions that must always be high or low to lead to high or low outcome states, but are not necessarily sufficient – and sufficient configurations, which represent combinations of conditions that lead to high or low outcome states. This method works with fuzzy-set memberships, which means that conditions and outcomes are represented in values ranging continuously from 0 (no membership equaling no concordance with the variable) to 1 (full membership equaling full concordance with the variable). We now explain the three steps we followed in our fsQCA: calibration, analysis for necessary conditions, and analysis for sufficient configurations.

Calibration. Using the calibration function of the QCA package in R (Duşa, 2019), we calculated the membership in fuzzy sets for the item mean of each construct. We set the calibration anchors to the 7-point Likert scale extrema and mean following recommendations from previous QCA research (Mattke, Maier, Weitzel, Gerow, & Thatcher, 2022): 1 for full non-membership, 4 for the cross-over point, and 7 for full membership. This calibration was applied to all seven constructs. Since fsQCA cannot operate with exact values of .50, we modified this value to .49999 for inclusion in the analysis.

Analysis for necessary conditions. Conditions are called necessary if their consistency exceeds the recommended consistency threshold of .90, the relevance of necessity (RoN) threshold of .60, and the coverage threshold of .60 (Mattke et al., 2021). Consistency is defined as the degree to which individuals in the same condition share the same outcome. Coverage describes the proportion of the sample being covered by a condition, and the RoN indicates whether a condition is relevant if necessary. Trivial necessary conditions (type 1 error) can be avoided by considering both coverage and RoN (Ragin, 2006).

Analysis for sufficient configurations. Since we considered both high and low continuance intention, we performed the following analysis steps for each outcome. First, we created a truth table of $2^6 = 64$ possible configurations of the six studied conditional constructs. Then, the truth table was reduced to avoid bias due to rare configurations by applying a frequency threshold of 3; that means that at least three datasets of participants must show this specific combination of conditions to be included in the resulting truth table. This is recommended for samples larger than 150 (Pappas & Woodside, 2021). We set the raw consistency threshold to .85 (Ragin, 2008). We fixed the threshold for proportional reduction of inconsistency (PRI) at .75 (Mattke et al., 2022) to prevent configurations from leading equally to low and high outcomes. We then applied the Quine-McCluskey algorithm to simplify the resulting truth table, which outputs conditions as irrelevant “don’t care” instances if they appear both high and low for a given configuration.

4.2. Results

Next, we present the results of the preliminary data analysis, the measurement model validation, and the fsQCA.

4.2.1. Preliminary data analysis and measurement model validation

We used Harman’s single-factor test to test for common method bias. The results of a principal component analysis indicated that a single factor explains 13.40 % of the variance in the data, which is below the recommended threshold of 50 %. The highest correlation between the constructs is .75 ($InM_{accomplish}$ x InM_{know}), below the threshold of .90 (Pavlou, Liang, & Xue, 2007). We used two items (“I like coffee.”, “I like tennis.”) for marker variable testing, and the highest bivariate correlation with any construct was .13, supporting the assumption of CMB absence (Lindell & Whitney, 2001).

Assuming a standard error of 0.15 for skewness, all variables except $InM_{accomplish}$ are significantly negatively skewed. As recommended for QCA studies (Pappas & Woodside, 2021), calibration anchors should be set according to the semantics of the scale rather than the distribution of the sample data to avoid bias. Therefore, we still apply the calibration procedure described above.

We validated the measurement model according to recent QCA studies (Mattke et al., 2021; Pappas & Woodside, 2021). The factor loadings of all items exceed the threshold of .707, supporting the assumption of indicator reliability (Carmines & Zeller, 1979); see Table 17 in the appendix. Construct reliability (CR) can be stated since the index values for all constructs are greater than .70, and their average variance extracted (AVE) is above .50 (see Table 2). Furthermore, the square root of each construct’s AVE is greater than each respective correlation with other constructs, indicating discriminant validity (Fornell & Larcker, 1981); the heterotrait-monotrait (HTMT) ratio test (Henseler, Ringle, & Sarstedt, 2015) underscores this conclusion, since the highest value (.83 for InM_{know} and $InM_{accomplish}$) is below the

Table 2
Descriptive, validity, and reliability statistics.

	Constructs		M	SD	CA	CR	AVE	1	2	3	4	5	6	7
1	**Intrinsic motivational factors**	Intrinsic motivation to accomplish	4.14	1.53	.92	.92	.74	**.86**						
2		Intrinsic motivation to know	4.58	1.52	.89	.90	.73	.83	**.86**					
3		Intrinsic motivation to experience stimulation	5.15	1.32	.94	.94	.84	.64	.65	**.92**				
4	**Extrinsic motivational factor**	Perceived usefulness	5.11	1.43	.97	.97	.82	.72	.53	.63	**.91**			
5	**Technology characteristics**	Perceived ease of use	5.59	0.97	.92	.92	.66	.45	.30	.38	.58	**.81**		
6		Perceived novelty	5.44	1.18	.89	.89	.74	.65	.54	.53	.74	.54	**.86**	
7	**Continuance intention**		5.16	1.39	.87	.88	.70	.59	.48	.40	.56	.32	.58	**.83**

Note: M = mean, SD = standard deviation, CA = Cronbach's α, CR = Composite reliability (ω_3), AVE = Average variance extracted; the bivariate correlation coefficients for the latent variable scores are displayed on the right side, the square root of AVE is listed on their diagonal.

$HTMT_{0.85}$ threshold. Therefore, the measurement model is valid, and fsQCA is feasible.

4.2.2. Necessary conditions and sufficient configurations

Necessary conditions. We identify high TeC_{PEOU} (consistency = .94, RoN = .62, coverage = .84) and high TeC_{NVL} (consistency = .92, RoN = .69, coverage = .86) as necessary conditions for high continuance intention; there is no evidence for necessary conditions leading to low continuance intention (see Table 3 and Table 4).

Sufficient configurations. We also found only sufficient configurations that explain high continuance intention (see Table 3). The first sufficient configuration (*inquisitive* user) describes individuals who are convinced by usefulness, novelty, and ease of use combined with intrinsic motivation to know. The second (*curious* user) represents individuals similar to the *inquisitive* user but seeking stimulation instead of knowledge. The third and fourth sufficient configurations (*extrinsically* and *comprehensively motivated* users) include individuals who expect both a perception of usefulness and ease of use and are motivated by either none or all three intrinsic factors. Individuals grouped by the fifth sufficient configuration (*passionate* user) are not driven by intrinsic motivation to accomplish but by the need to know and to experience stimulation in addition to a perception of novelty and ease of use.

We assessed the overall quality of these solutions based on their coverage and consistency (Ragin, 2006). Scores of .84 (coverage) and .92 (consistency) indicate high explanatory power. For all sufficient solutions, the consistency scores exceed the threshold of .75, and their respective row coverages ranging from .27 to .79 show empirical relevance. All sufficient configurations identified in this analysis have unique coverage scores ranging from .01 to .08 and uniquely contribute to high continuance intention.

An additional check for necessity relations – meeting the recommended thresholds for necessary conditions outlined in Section 4.1.3 – reveals that two dyadic relations include low TeC_{NVL}; see Table 4. Combining these necessity relations results in rare (each with $n = 4$) but highly consistent sufficient configurations, including low TeC_{NVL} (see Table 5). Therefore, after the simplification with the Quine-McCluskey, the necessary condition high TeC_{NVL} is leveled out in the two sufficient configurations *extrinsically motivated* and *comprehensively motivated* – it is a so-called hidden necessary condition in these two configurations (Schneider & Wagemann, 2012).

Table 4
Selection of necessity relations for high continuance intention.

Conjunctions	Consistency	RoN	Coverage
ACP*STI	.91	.75	.88
ACP*XPU	.90	.78	.89
KNW*STI	.92	.73	.88
~KNW*XPU	.93	.64	.84
KNW*XPU	.93	.72	.88
~STI*XPU	.92	.69	.86
STI*XPU	.95	.68	.87
STI*~NVL	.91	.70	.86
XPU*~NVL	.91	.72	.87

Note: The tilde (~) indicates low-level conditions, and the asterisk (*) is used to separate conjunctions; abbreviations used for Boolean algebra are ACP = $InM_{accomplish}$, KNW = InM_{know}, STI = $InM_{stimulation}$, XPU = ExM_{PU}, and NVL = TeC_{NVL}.

4.2.3. Validation and robustness of the results

We tested the sensitivity of the solutions to both the sample and the calibration. First, setting the frequency threshold to four showed no significant discrepancy with the original solution, except that the high

Table 3
Necessary conditions and sufficient configurations for high and low continuance intention.

		Continuance intention					
		HIGH					LOW
		Inquisitive	Curious	Extrinsically motivated	Comprehensively motivated	Passionate	–
Intrinsic motivational factors	Intrinsic motivation to accomplish			○	●	○	no results
	Intrinsic motivation to know	●		○	●	●	
	Intrinsic motivation to experience stimulation		●	○	●	●	
Extrinsic motivational factor	Perceived usefulness	●	●	●	●		
Technology characteristics	Perceived ease of use	★	★	★	★	★	
	Perceived novelty	★	★			★	
Raw coverage		.70	.79	.27	.62	.40	–
Unique coverage		.01	.08	.01	.01	.02	–
Consistency		.93	.93	.95	.94	.94	–
Solution coverage		.84					–
Solution consistency		.92					–

Note: Black circles (●) indicate high levels of motivational factors and technology characteristics, white circles (○) indicate low levels, black stars (★) indicate necessary conditions, and blank spaces ( ) indicate a "don't care" instance.

Table 5
Selection of sufficient configurations for high continuance intention before simplification of the truth table.

	Extrinsically motivated		Comprehensively motivated	
$InM_{accomplish}$	○	○	•	•
InM_{know}	○	○	•	•
$InM_{stimulation}$	○	○	•	•
ExM_{PU}	•	•	•	•
TeC_{PEOU}	•	•	•	•
TeC_{NVL}	•	○	○	•
Consistency	.96	.96	.95	.95
PRI	.84	.77	.81	.92

Note: White circles (○) indicate low levels, and black circles (•) indicate high levels of motivational and technology characteristics.

expression of InM_{know} in the first solution was replaced by a low expression of $InM_{accomplish}$. We then repeated the analysis with calibrations to anchor values of 1.5, 4, and 6.5, as well as 2, 4, and 6; here, all, respectively, the first four solutions remained. Overall, the five solutions (see Table 3) prove to be predominantly robust.

5. Study 2: Qualitative interview study

To complement and illustrate the findings of Study 1, we conducted an additional qualitative study consisting of semi-structured interviews with 15 participants. We aimed to find use cases matching the sufficient configurations of Study 1 and to identify alternative explanations for low continuance intention.

5.1. Method

The following describes the sample collection, characteristics, interview structure, and analysis.

5.1.1. Data collection and sample

The interview sample comprises 15 participants recruited from the authors' circles and connected circles through snowballing recommendations. All interviewees hold a Master's degree or equivalent and are located in Germany; additional demographic information is presented in Table 6. Participation was subject to informed consent and at least one-time use of ChatGPT for private or work purposes. We conducted the interviews nine months after the data collection of the first quantitative study and, therefore, one year and three months after the public release of ChatGPT.

93.33 % of the participants indicate that ChatGPT is their most used AI application; additional quantitative data about their AI and ChatGPT usage is presented in Table 7. Nine interviewees used ChatGPT as their first consciously used AI application or were introduced to AI by ChatGPT; 12 interviewees used ChatGPT for the first time within three months of its release. While most participants state they do not use it in private (60.00 %), nearly half of them use ChatGPT daily at work (46.67 %).

Table 7
Detailed information on AI and ChatGPT usage.

Time since first conscious use of an AI application (in months) Median: 15		Time since the first use of ChatGPT (in months) Median: 14		Frequency of ChatGPT use in private (in percent)		Frequency of ChatGPT use at work (in percent)	
9	13.33	9	20.00	never	53.33	1 / m.	6.67
14–15	46.67	12–14	33.33	1 / m.	13.33	1 / w.	13.33
18–24	13.33	15	46.67	1 / 2w.	13.33	2 / w.	13.33
48	6.67			1 / w.	6.67	3 / w.	20.00
72	6.67			daily	13.33	daily	46.67
120	13.33						

Note: Frequency of use categories are derived from the free responses given by those surveyed; 1 / m. = up to once a month, 1 / 2w. = once every second week, 1 / w. = up to once a week, 2 / w. = up to twice a week, 3 / w. = up to three times a week.

5.1.2. Interview structure and analysis

We conducted semi-structured interviews with an average duration of about 20 minutes. Questions about general ChatGPT usage behavior, specific usage situations in private and at work, the participants' continuance intention, and their understanding of extrinsic motivation are framed by an introductory and a concluding question about previous and possible future influences of ChatGPT on the interviewees' everyday life; for the detailed interview guide, see Table 18 in the Appendix. As the interviews were semi-structured, the procedure followed the described guide but allowed for additional questions or queries from the participants. A pilot interview resulted in minor revisions, while informational and structural similarity to the final guide made integration into the data sample possible. After conducting the 15 interviews, we transcribed them using a privacy-compliant offline audio-to-text transcription application.

5.1.3. Coding

First, we deductively coded according to the five topics of interest that we obtained from the first study. These were also the basis for the development of the interview guide: use cases in work and private contexts, facilitating and hindering factors for ChatGPT use, and additional extrinsic motivational factors. The labels within these topics were then inductively sorted and aggregated into themes (use cases) or factors (factors); see Fig. 3. At the same time, we analyzed every mentioned use case according to our research model and the configurational approach of Study 1; we applied this procedure for every participant separately so the same use case can be characterized by different sufficient configurations of the examined motivational factors and technology

Table 6
Demographics of 15 interview participants.

Age (in percent) Mean: 29.53, SD: 6.06, Range: 24–48		Gender (in percent)		Job in IT (in percent)		Other AI applications in use (in percent)	
< 25	6.67	Female	33.33	No	40.00	DeepL	40.00
25–34	80.00	Male	66.67	Yes	60.00	Grammarly	20.00
35–44	6.67	Nonbinary	0.00			DALL-E	13.33
45–54	6.67					Google Bard / Gemini	13.33
						GitHub Copilot	6.67
						others (academic work)	20.00
						others (image generation)	13.33
						others (organization tools)	13.33

Note: GER = Germany; E1 = Elementary or primary education, E2 = Lower secondary education (approximately 5 to 10 years), E3 = Higher secondary education (11 to 13 years), E4 = Non-academic professional degree, E5 = Bachelor's degree or equivalent level, E6 = Master's degree or equivalent level, E7 = Doctoral degree or equivalent level.

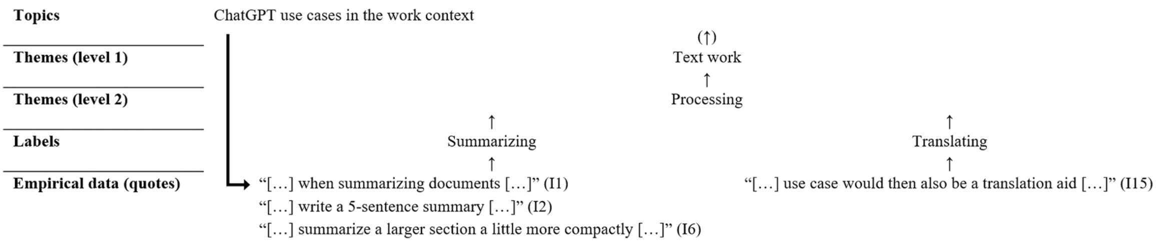

Fig. 3. Coding scheme for ChatGPT use cases in the work context (scheme adapted from Stein, Newell, Wagner, & Galliers, 2015).

characteristics, but use cases were only counted once for every participant, even if mentioned several times.

5.2. Results

Here, we outline the results of the interview data analysis. First, we give an overview of 69 mentions of ChatGPT use cases, differentiated between 54 mentions with 16 labels in the work context and 15 mentions with 11 labels in the private context, as well as their assignment to the different conditional factors and sufficient configurations derived from Study 1. Then, we present alternative facilitating and hindering factors for ChatGPT use, related extrinsic motivational factors, and information about the participants' continuance intention. All interviewee quotes cited in the following are translated from German by the authors.

5.2.1. Use cases differentiated by context

Regarding the work context, we extracted 16 different use cases for ChatGPT from 54 mentions; see Table 8 for details. The most frequently assigned label is Coding aid (60.00 % of the participants mentioned a corresponding use case; see use case 11 in Table 9) – for example, participants stated: "For programming, when you have bugs where you can't get further. I recently had to code in JavaScript, which I never learned. It was a great help because it probably wasn't difficult code" (I2). Other interviewees mentioned Language editing / Rephrasing (46.67 %, use case 1) – "I simply put in a finished text again and say that it should be shorter or maybe just sound different, I don't quite like the language yet, that's how I use it" (I10) –, Idea generation (46.67 %, use case 8) – "Even if you have creative work like that, you can also just say, give me 20 ideas. Of those, 19 are crap, but there might be one where you say I can build on it" (I4) –, and Creation aid for work materials (46.67 %, use case 12) – "But of course making slides, making videos, general stuff like that - the classic busy work where you have to spend a lot of time creating something that's already in your head somewhere" (I4). Some rarer use cases (numbers 2, 5, 14, and 16) might need further explanation: One participant each mentioned that they use ChatGPT to format text via LaTeX, to generate different solution suggestions for IT helpdesk requests, to find examples for complex or unknown constructs, and to check if their research ideas have already been covered, since ChatGPT would in the opposite case only output generic information.

For the private context, we found 11 use cases covering 15 mentions; see Table 9 for details. Although notably fewer interviewees use ChatGPT for non-professional purposes, the private use cases are similarly diverse, with most of the participants using the application for Specific recommendations (26.67 %, use case 1), e.g., vacation – "But

Table 9
Classification of ChatGPT use cases in the private context.

Use cases	Themes	Labels	Number of mentions	
1	Starting point	Specific recommendations	4 (26.67 %)	5
2		General idea generation	1 (6.67 %)	
3	Information	Complex research	1 (6.67 %)	3
4		News	1 (6.67 %)	
5		Simple search query	1 (6.67 %)	
6	Learning	Homework assistance	1 (6.67 %)	3
7		Language learning	1 (6.67 %)	
8		Structuring areas of interest	1 (6.67 %)	
9	Text work	Writing an email / a greeting card	2 (13.33 %)	3
10		Pre-formulating text	1 (6.67 %)	
11	Self-optimization	Planning aid	1 (6.67 %)	1

Note: The percentages indicate how many participants mentioned a use case corresponding to the respective label. As participants can mention different use cases from the same theme, the aggregated numbers of mentions are not expressed in percentages in relation to the sample size.

Table 8
Classification of ChatGPT use cases in the work context.

Use cases	Themes		Labels	Number of mentions	
1	Text work	Editing	Language editing / Rephrasing	7 (46.67 %)	21
2			Formatting assistance	1 (6.67 %)	
3		Writing	Pre-formulating text	4 (26.67 %)	
4			Writing emails/posts	2 (13.33 %)	
5			Solutions for service inquiries	1 (6.67 %)	
6		Processing	Summarizing	5 (33.33 %)	
7			Translating	1 (6.67 %)	
8	Starting point		Idea generation	7 (46.67 %)	10
9			Suggesting structure	2 (13.33 %)	
10			Initial research	1 (6.67 %)	
11	Programming		Coding aid	9 (60.00 %)	9
12	Work materials		Creation aid	7 (46.67 %)	7
13	Explanatory uses		Explanation	3 (20.00 %)	4
14			Exemplification	1 (6.67 %)	
15	Data analytics		Analysis assistance	2 (13.33 %)	2
16	Verification		Testing for established knowledge	1 (6.67 %)	1

Note: The percentages indicate how many participants mentioned a use case corresponding to the respective label. As participants can mention different use cases from the same theme, the aggregated numbers of mentions are not expressed in percentages in relation to the sample size.

otherwise also for things like writing me a travel list or somehow a travel plan" (I11) or "[…] when traveling and finding out about countries" (I14), presents – "It starts with ideas for gifts, for example. I sometimes use ChatGPT to brainstorm ideas. I find that very practical, especially if you also add a local reference" (I12), or cooking – "I have tried it from time to time, most likely for cooking" (I7) –, and for Writing an email or a greeting card (13.33 %, use case 9) – "Otherwise maybe if you have to write emails privately or something like that" (I2). Also, here are rather specific use cases, for example, numbers 3, 6, 7, 8, and 11. In our interview, one ChatGPT user each mentioned that they use the application for research that would be too complex to be performed with regular search engines, to solve homework assignments for their children, to learn a new language through the generation of vocabulary lists or conjugation schemes, to structure a high amount of information in an area of interest making it more comprehensible, and to help with self-optimization by creating training plans.

5.2.2. Use cases in relation to sufficient configurations

We analyzed the use cases derived from the interviews regarding the conditional factors from our research model; see Table 10 for details. In both contexts, work and private, ExM_{PU} – for example mentioned as "increase in efficiency" (I9) – and TeC_{PEOU} – most interviewees called the application literally "easy" (I12) to use – are the most mentioned relevant factors, and TeC_{NVL} is the least mentioned relevant factor. TeC_{NVL} is also the most mentioned irrelevant factor – especially in private use – and simultaneously the most not-mentioned factor across both contexts; one participant stated about the influence of novelty: "In the beginning, I think so, yes. It was almost exciting" (I3).

The assignment of the use cases from Study 2 to the sufficient configurations of Study 1 revealed twofold. First, the *inquisitive* user is the most mentioned configuration (34.78 % of all use cases); one participant described a simple search query with ChatGPT – "I need the info, tell me and maybe a link to a website" (I2) – as characterized by knowledge acquisition, usefulness, ease of use, and novelty. This configuration is followed by the *curious* user (23.18 %); one participant reported that using ChatGPT for specific recommendations – "Even if you have ideas about what you could do at the weekend or something like that, any unusual activities" (I12) – was stimulating, partly because of the pace of text generation – "I also like the fact that it generates so slowly and that you can read along in real time" (I12). Together, these two configurations account for almost half of all use cases (44.93 % as they share nine use cases). Second, the distribution of conditional factors (Table 10) is also reflected in the mentioned configurations, as TeC_{NVL} is mostly absent. Therefore, we differentiate the evaluation according to possible levels of TeC_{NVL}, see Table 11. In total, the sufficient configurations from Study 1 can account for more than half of the mentioned use cases in Study 2 (37 equaling 53.62 %), 32 mentions of use cases could not be assigned due to insufficient descriptions by the participants, who sometimes mentioned a use case only briefly or could not provide detailed information about it.

5.2.3. Facilitating and hindering factors

The participants provided information on four facilitating factors for the use of ChatGPT with 12 facets and a total of 21 mentions. In particular, they rated the structure and organization of the information processing as positive – "Yeah, I think it's cool that ChatGPT breaks it down in a very structured way because ideas are something very spongy and it can organize them relatively well and that the answers are also well organized" (I7). Furthermore, they approve of the coherence of interaction – "Then it often knows which text is meant based on the context and so on, and I think that's very cool, for example" (I13) –, and the application's inventiveness, namely creativity – "[B]ecause when I'm under time pressure and pressure in general, I'm not so creative, and then I need support and then again I would use ChatGPT" (I12) –, as well as originality – as seen, for example, in "thought-provoking impulses" (I1); see Table 12.

In contrast, the interviewees mentioned considerably more hindering factors: 29 facets of eight factors with a total number of mentions of 61. In particular, the participants complained about a lack of output reliability – "[B]ut above all hallucinations, that you recognize them and that you somehow, actually, process them accordingly" (I6) –, the obscure and arguably incorrect database – "In other cases, there is no access and no sources can be provided" (I14) –, and the process of turning circles in the interaction with the application – "Then you reformulate the query ten more times and end up back where you started" (I15). More than half of them raised privacy concerns such as: "No, I probably would not use it if I had to enter any of my sensitive data because it would be saved" (I2); see Table 13.

5.2.4. Extrinsic motivation and continuance intention

When asked to identify additional sources of extrinsic motivation besides ExM_{PU}, the participants named six factors with 14 facets and a total of 29 mentions. In particular, social aspects such as comparison with peers – "[J]ust to know, so to speak, also to be with others. And I would say it gives you more of a sense of security" (I9) –, the need for efficiency due to high workloads – "So for me it would always be a capacity issue. So, the more limited the capacity, the more I would look for ChatGPT solutions" (I13) –, expectations from superiors – "[O]r just from the manager. To me, that would be extrinsic motivation. And from my point of view, that would also lead to people using it, even though they might not use it of their own accord" (I15) –, the lack of a functional alternative – "But looking at the market in this way, it is unlikely that other major players will quickly overtake OpenAI" (I14) –, or the need to keep up with technological progress – "Because I believe that if you miss such important developments, it will be very difficult to keep up with these issues" (I5) – emerged as motivating forces; see Table 14.

Four interviewees identified ExM_{PU} as an extrinsic motivational factor – "The benefit comes from the fact that somehow I have an external task or an expectation that I want to fulfill, and I want to do it as well or as quickly as possible, whatever the case may be, and that's why I use the application" (I10) –, two did not comment, and three were undecided; of the remaining six participants, only three reported being self-motivated by efficiency – "I mean, if it's useful, it's fun, and then I'm

Table 10
Mentions of motivational factors and technology characteristics in use case descriptions.

		$InM_{accomplish}$	InM_{know}	$InM_{stimulation}$	ExM_{PU}	TeC_{PEOU}	TeC_{NVL}
Relevant	**Work**	15 (27.78 %)	20 (37.04 %)	9 (16.67 %)	45 (83.33 %)	40 (74.07 %)	5 (9.26 %)
	Private	7 (46.67 %)	8 (53.33 %)	7 (46.67 %)	11 (73.33 %)	11 (73.33 %)	1 (6.67 %)
	Total	22 (31.88 %)	28 (40.58 %)	16 (23.19 %)	56 (81.16 %)	51 (73.91 %)	6 (8.70 %)
Irrelevant	**Work**	10 (18.52 %)	10 (18.52 %)	12 (22.22 %)	2 (3.70 %)	0 (0.00 %)	11 (20.37 %)
	Private	1 (6.67 %)	3 (20.00 %)	3 (20.00 %)	0 (0.00 %)	0 (0.00 %)	8 (53.33 %)
	Total	11 (15.94 %)	13 (18.84 %)	15 (21.74 %)	2 (2.90 %)	0 (0.00 %)	19 (27.54 %)
No statement	**Work**	29 (53.70 %)	24 (44.44 %)	33 (61.11 %)	7 (12.96 %)	14 (25.93 %)	38 (70.37 %)
	Private	7 (46.67 %)	4 (26.67 %)	5 (33.33 %)	4 (26.67 %)	4 (26.67 %)	6 (40.00 %)
	Total	36 (52.17 %)	28 (40.58 %)	38 (55.07 %)	11 (15.94 %)	18 (26.09 %)	44 (63.77 %)

Note: The percentages are relative to the respective number of mentions (54 for "Work", 15 for "Private", and 69 for "Total").

Table 11
Assignment of use cases to sufficient configurations.

Sufficient configurations	Work			Private			Total
TeC_{NVL}:	•	○		•	○		
Inquisitive user KNW*XPU*PEU*NVL	–	5	11	1	7	–	24 (34.78 %)
Curious user STI*XPU*PEU*NVL	–	1	8	–	5	2	16 (23.18 %)
Extrinsically motivated ~ACP* ~KNW* ~STI*XPU*PEU	1	4	1	–	–	–	6 (8.70 %)
Comprehensively motivated ACP*KNW*STI*XPU*PEU	–	1	–	–	5	–	6 (8.70 %)
Passionate user ~ACP*KNW*STI*PEU*NVL	–	–	3	–	–	–	3 (4.35 %)

Note: The tilde (~) indicates low-level conditions, and the asterisk (*) is used to separate conjunctions; abbreviations used for Boolean algebra are ACP = $InM_{accomplish}$, KNW = InM_{know}, STI = $InM_{stimulation}$, XPU = ExM_{PU}, PEU = TeC_{PEOU}, and NVL = TeC_{NVL}; the percentages in the column "Total" are relative to all (69) mentioned use cases.

Table 12
Facilitating factors for the use of ChatGPT.

Facilitating factors	Facets = labels	Number of mentions	
Information processing	Structure / Organization	2 (13.33 %)	5
	Accuracy	1 (6.67 %)	
	Compactness	1 (6.67 %)	
	Extent of database	1 (6.67 %)	
Interaction	Coherence	2 (13.33 %)	5
	Contextuality	1 (6.67 %)	
	Pace	1 (6.67 %)	
	Vocality	1 (6.67 %)	
Inventiveness	Creativity	2 (13.33 %)	4
	Originality	2 (13.33 %)	
Authority	Safeguarding	1 (6.67 %)	2
	Superiority	1 (6.67 %)	

Note: The percentages indicate how many of the participants mentioned a facet corresponding to the respective label. As participants can mention different facets from the same facilitating factor, the aggregated numbers of mentions are not expressed in percentages in relation to the sample size.

happy to do it" (I2) –, and the other three reported being goal-oriented – "Because I know what I need to work better" (I7) – and therefore also extrinsically motivated by ExM_{PU}. This confirms that we classified ExM_{PU} as a motivational rather than a technology-centered factor. When asked in which domain ExM_{PU} is more relevant, 12 participants chose work, and one person even denied the need for ExM_{PU} in private; here, one interviewee did not comment, and two were undecided. Taking the private and work contexts together, twelve participants indicated that ExM_{PU} is the most relevant factor in using ChatGPT – "So let's say we have effectiveness and productivity as an overall goal" (I14); one interviewee did not comment, and three were undecided. This also confirms the choice of ExM_{PU} as the sole extrinsic motivational factor.

Four of the six participants who use ChatGPT in private intend to continue using it; one person is undecided, and one person plans to switch applications. The same interviewee who indicates switching to another application in private will do so for work, and all other participants intend to continue using ChatGPT in this context.

6. Discussion

GenAI is profoundly reshaping how users perceive and interact with technology. There is a significant need to build on cumulative knowledge about AI (Collins, Dennehy, Conboy, & Mikalef, 2021) to develop insights into the individual use of GenAI applications such as ChatGPT. We argue that there is a specific need to understand the complex interactions of motivational and technology characteristics and how these lead to high and low continuance intention. Therefore, we conducted a mixed-methods study in the form of a fsQCA with survey data from 279 ChatGPT users, complemented by qualitative data from 15

Table 13
Hindering factors for the use of ChatGPT.

Hindering factors	Facets = labels	Number of mentions	
Bad output	Lack of reliability	5 (33.33 %)	18
	Expectability	4 (26.67 %)	
	Poor quality	3 (20.00 %)	
	Unmet expectations	3 (20.00 %)	
	Illogicality	1 (6.67 %)	
	Poor verifiability	1 (6.67 %)	
	Unmet scientific claim	1 (6.67 %)	
Doubtful database	Obscurity / Incorrectness	5 (33.33 %)	10
	Poor actuality	3 (20.00 %)	
	Copyrights / Plagiarism	2 (13.33 %)	
Data governance	Privacy concerns	8 (53.33 %)	10
	IT security concerns	1 (6.67 %)	
	Unclear system integration	1 (6.67 %)	
Problematic interaction	Turning in circles	3 (20.00 %)	7
	Answers too long	1 (6.67 %)	
	Format dependency	1 (6.67 %)	
	Need for specificity	1 (6.67 %)	
	Unstructuredness	1 (6.67 %)	
Restricted access	Costs	2 (13.33 %)	5
	Insufficient quota/capacity	2 (13.33 %)	
	"Freemium" model	1 (6.67 %)	
Personal attitude	Reduced learning	2 (13.33 %)	4
	Anticyclical skepticism	1 (6.67 %)	
	Ecology	1 (6.67 %)	
Personal contribution	Requirement	2 (13.33 %)	4
	Inauthenticity	1 (6.67 %)	
	Mandatory declaration	1 (6.67 %)	
Regulations	Legal regulations	2 (13.33 %)	3
	Professional regulations	1 (6.67 %)	

Note: The percentages indicate how many of the participants mentioned a facet corresponding to the respective label. As participants can mention different facets from the same hindering factor, the aggregated numbers of mentions are not expressed in percentages in relation to the sample size.

semi-structured interviews. Based on combined findings (see Table 15), we draw meta-inferences and thereby develop five propositions (P), discuss theoretical contributions and practical implications, report the studies' limitations, and highlight opportunities for future research.

6.1. Synthesis, meta-inferences, and propositions

Causal asymmetry: The research results from Study 1 suggest five sufficient configurations, including two necessary conditions, that lead to *high* continuance intention among ChatGPT users. In contrast, we find no sufficient configurations leading to *low* continuance intention. This is particularly interesting from the perspective of complex conjunctural interrelations between factors resulting in causal asymmetry (Mattke et al., 2021); the inversion of independent variables does not have to cause an inversion of the outcome variable. We explain this by referring

Table 14
Extrinsic motivational factors for the use of ChatGPT.

Extrinsic motivational factor	Facets = labels	Number of mentions	
Social aspects	Peer comparison	5 (33.33 %)	9
	Hype	3 (20.00 %)	
	Recommendation	1 (6.67 %)	
Efficiency / Effectiveness	High workload	3 (20.00 %)	6
	Benchmarking	1 (6.67 %)	
	Overwhelming tasks	1 (6.67 %)	
	Scientific proof	1 (6.67 %)	
Professional requirements	Expectation from superiors	5 (33.33 %)	5
Lack of alternatives	No functional alternative	2 (13.33 %)	4
	First application introduced	1 (6.67 %)	
	No open-source alternative	1 (6.67 %)	
Technological progress	Keeping pace	2 (13.33 %)	3
	Claim for topicality	1 (6.67 %)	
Competitiveness	Educational	1 (6.67 %)	2
	Entrepreneurial	1 (6.67 %)	

Note: The percentages indicate how many participants mentioned a facet corresponding to the respective label. As participants can mention different facets from the same extrinsic motivational factor, the aggregated numbers of mentions are not expressed in percentages in relation to the sample size.

Table 15
Summary of combined research findings.

Quantitative survey study	Identification of five sufficient configurations and two necessary conditions for high individual ChatGPT continuance intention, considering motivational factors and perceptions of technology characteristics related to innovation. Confirmation of the weaker influence of the intrinsic motivation to accomplish compared to other intrinsic motivational factors. Evidence for the combined positive influence of perceived usefulness and perceived ease of use on individual ChatGPT continuance intention.
Qualitative interview study	Identification of 27 individual use cases for ChatGPT in private and work contexts. Identification of additional facilitating and hindering factors for individual ChatGPT continuance intention. Confirmation of the relevance of perceived usefulness and perceived ease of use for individual ChatGPT continuance intention. Evidence for the diminishing influence of perceived novelty on individual ChatGPT continuance intention over time.
Meta-inference	Differentiation of the identified conditions and configurations considering the use context. Linking the configurations of motivational factors and technology characteristics to actual individual use cases. Enriching the identified configurations with additional facilitating and hindering factors, and exploring relationships between them. Building a comprehensive understanding of extrinsic motivation for individual ChatGPT use.

to different characteristics of the studied factors. They typically encourage IS use (Li et al., 2013; Wells et al., 2010), which means that a low expression of these factors may lead to an ambivalent but not low level of continuance intention. This points to the need to study factors that hinder continuous use (Cenfetelli & Schwarz, 2011), such as hindrance IS use stress (Maier, Laumer, Tarafdar et al., 2021), which we incorporated in Study 2. The interviews revealed that factors hindering the continued use of ChatGPT mainly belong to the domains of quality – of output, database, and interaction – and data governance. ExM_{PU} and TeC_{PEOU} may coincide with these hindering factors regarding content, but the usage experience still seems to be predominantly positive, so most participants indicated their intention to continue using ChatGPT. Several interviewees reported that they notice quality problems, but they are able to cope with them as long as there is constant improvement or at least no deterioration. Therefore, we propose the following:

> **P1**: Intrinsic and extrinsic motivational factors, perceived ease of use, and perceived novelty together explain high continuance intention, while hindering factors, such as poor output, database, and interaction quality as well as data governance issues need to be considered to also explain low continuance intention.

Necessary conditions with different persistence: We took into account that ChatGPT is an innovative technology that users need to become familiar with, and therefore, we considered two related technology characteristics to be important for continuance intention, namely TeC_{PEOU} and TeC_{NVL}. The results of Study 1 underscore the importance of TeC_{PEOU} by showing that it is a necessary condition and part of every sufficient configuration leading to high continuance intention. Considering private use, TeC_{PEOU} is relevant since users expect an IS to require less mental effort. In this sense, ChatGPT's ability to process and output natural language makes it easy to use because it differs from other IS, such as non-GenAI search engines, which require users to invest more mental effort in formulating queries. Thus, reducing effort through ease of use leads to high continuance intention. This was also shown in Study 2 as TeC_{PEOU} is the second most mentioned factor for using ChatGPT, and almost all facilitating factors falling into the most mentioned categories of information processing and interaction are related to ease of use. TeC_{PEOU} seems to be a key feature of ChatGPT that differentiates it from other technologies. There is not much need for familiarization in the sense of learning how to use it, but rather in the effortlessness of using it. The implementation of NLP results in a user experience that is so uniquely easy that it is perceived as strikingly simple. As long as natural language is not the standard of user interaction, IS such as ChatGPT are likely to be perceived as easy to use, which maintains this positive influence on continuance intention. Moreover, the novelty of ChatGPT allows us to investigate whether TeC_{NVL} influences continuous intention. Previous research has emphasized the relevance of TeC_{NVL} for positive perceptions of technology (Rutten & Geerts, 2020), and the results of Study 1 highlight this by showing that it is a necessary condition for high continuance intention. While participants in Study 2 stated that they might use a new IS to keep pace with technological progress and, for social reasons, to be part of technological trends, TeC_{NVL} showed substantially less relevance as an isolated factor and as part of sufficient configurations. We attribute this to the fact that ChatGPT had been available for more than a year at the time of data collection, and most interviewees reported using it for almost all of that time. This has probably led to ChatGPT being perceived as less new to the participants and, therefore, TeC_{NVL} less relevant to their continuance intention. In addition, the interviewees attributed the arguments for keeping pace to extrinsic motivation induced by society rather than to the technology's characteristics. With this, we propose:

> **P2**: Perceived ease of use is a persistent and necessary condition for high continuance intention, demonstrated across multiple sufficient configurations, while perceived novelty initially contributes to continuance intention but its influence diminishes over time as users become familiar with the IS.

Complementarity in intrinsic motivational factors: As a result of Study 1, high InM_{know} (*inquisitive* user) or $InM_{stimulation}$ (*curious* user) combined with ExM_{PU}, TeC_{PEOU}, and TeC_{NVL} are each sufficient to explain high continuance intention. $InM_{accomplish}$, however, does not show this configurational pattern; it only appears with other intrinsic motivational factors (see Table 3). In addition, $InM_{accomplish}$ shows another notable deviation from other observed configurations. $InM_{accomplish}$ is low for *passionate* users, while InM_{know} and $InM_{stimulation}$ need to be high – a complimentary combination of the *inquisitive* and *curious* configurations seems to be sufficient to compensate for low levels of $InM_{accomplish}$. This is consistent with previous findings that $InM_{accomplish}$ has a less significant influence on various behaviors of continued use than other motivational factors (Li et al., 2013), considering that continuance is associated with usage that has already been accomplished. This means that a need for knowledge acquisition or experienced stimulation through use – given ExM_{PU}, TeC_{PEOU}, and TeC_{NVL} – can lead to continuance intention for ChatGPT use, while a desire for accomplishment does not have the same effect. From a theoretical perspective, the decreasing influence of TeC_{PEOU} found in previous research (Yeh & Teng, 2012) may be expressed in the subordinate role of $InM_{accomplish}$ in our survey study. Users might still prefer the usability of this novel technology, but they assume that they have accomplished the functionality of ChatGPT. This lower explanatory relevance of $InM_{accomplish}$ is partly reflected in the results of Study 2. Here, it shows a lower relevance in terms of mentions than InM_{know} but a higher relevance than $InM_{stimulation}$. This could be explained by the more private association of $InM_{stimulation}$, so overall, fewer mentions could be counted for $InM_{stimulation}$ as the participants mainly reported use cases related to work. Furthermore, interviewees might have often confused $InM_{accomplish}$ with goal orientation and, therefore, an aspect of ExM_{PU}, which could have led to a disproportionate number of $InM_{accomplish}$ counts. In fact, only a single use case can be primarily associated with $InM_{accomplish}$, namely self-optimization in the private context. Taken together, we propose:

P3: The intrinsic motivations to know and to experience stimulation, combined with perceived ease of use, perceived novelty, and extrinsic motivation, are more relevant for high continuance intention than the intrinsic motivation to accomplish, and together, they can complementarily compensate for low levels of the latter.

Perceptions of usefulness and ease of use are key for ChatGPT usage: ExM_{PU} and TeC_{PEOU} influence IS usage behavior (Cenfetelli & Schwarz, 2011; Mishra, Shukla, Rana, Currie, & Dwivedi, 2023). The analysis of Study 1 reflects this by showing that ExM_{PU} is a part of four configurations that lead to high continuance intention among ChatGPT users, and TeC_{PEOU} is even a necessary condition. Focusing on the configurations of *extrinsically motivated* and *comprehensively motivated* users, we notice that the constant is that high values of ExM_{PU} and TeC_{PEOU} are present in both groups (see Table 3). Thus, these users have in common that they continue to use ChatGPT because they subjectively perceive it as useful and easy to use. The combination of ExM_{PU} and TeC_{PEOU} may be an example of a mutual influence effect of motivational factors and technology characteristics, such that together, they lead to a level of continuance intention that is high enough to render the collective high or low levels of intrinsic motivation irrelevant. ExM_{PU} and TeC_{PEOU} are usually perceived as critical facilitators in work contexts (Hess et al., 2014). In this sense, *extrinsically motivated* users also apply these categories of positive IS characteristics to their private use. Also, in Study 2, ExM_{PU} and TeC_{PEOU} showed particularly high relevance for continuance intention as they received the most mentions of all factors investigated, independent of the context. When asked about additional extrinsic motivators, many interviewees cited the need to be efficient and effective, especially in the work context, which ultimately calls for a useful and easy-to-use IS. With this, we propose:

P4: Perceived usefulness and perceived ease of use are predominant factors in configurations that lead to high continuance intention, surpassing intrinsic motivational factors.

Different contexts require different configurations: The influence of motivational factors on behavior depends on the context (Vallerand, Fortier, & Guay, 1997). In Study 1, we examined the configurations of motivational factors and technology characteristics independently of context, resulting in the finding of equifinality. Since the configurations are clearly different, we aimed to explain part of this divergence by including a distinction between work and private life in the interviews of Study 2. Indeed, the associated use cases differ – both share the use for initiating thoughts or actions, but at work, resource- and capacity-intensive tasks dealing with texts dominate. On the level of configurations, the private context shows a relatively higher share of *comprehensively motivated* users. On the level of conditions, this is covered by relatively higher shares of all three intrinsic motivations. Since extrinsic motivational factors – e.g., payment, direction, need to perform – may dominate the work context, an intrinsic overhang in the private context is not surprising, since behavior can be chosen more deliberately there. Most interviewees also indicated that extrinsic motivation is more relevant to them in work contexts. With that, we propose:

P5: The configurations that lead to high continuance intention differ between work and private contexts, with intrinsic motivational factors having a relatively stronger influence on private usage, while extrinsic motivation is more decisive in work settings.

6.2. Theoretical contributions and implications

With the importance of studying ChatGPT usage from an individual perspective, our paper makes several contributions to the research on GenAI and ChatGPT as well as continuance intention.

First, AI-related research has focused on strategic and organizational use (Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021; van den Broek, Sergeeva, & Huysman Vrije, 2021). We extend the existing literature by contextualizing our study to individual use (Hong et al., 2014) and with a perspective on private and work-related ChatGPT use. Our findings contribute that the factors influencing usage behavior differ at the individual level, ranging from intrinsic to extrinsic motivation, and include technology characteristics of novelty and usefulness. By revealing these insights, we initiate a new research direction that points to the need for further investigation of GenAI and, in particular, ChatGPT usage at the individual level.

Second, the findings also allow us to explain causal asymmetry. We propose that there is causal complexity at the level of both condition and outcome realization. The inversion of configurations leading to high ChatGPT continuance intention does not imply low continuance intention; similarly, high and low conditions of factors can contribute to configurations that equally lead to high continuance intention among ChatGPT users. Our results show that the four motivational factors and the two technology characteristics considered cannot systematically explain low outcome values (P1). Considering the complex nature of configurations and especially the causal asymmetry revealed by our analysis, we recommend extending explanatory models by adding specific hindering factors such as use stress (Maier, Laumer, Tarafdar et al., 2021) or critical incidents (Kari, Salo, & Frank, 2020) to help explain low continuance intention. Furthermore, our results indicate the need to consider the influence of satisfaction. In particular, ExM_{PU} and TeC_{PEOU} have a positive effect on continuance intention. However, potentially low levels of these variables do not fully capture the dissatisfaction with output, data, or interaction quality reported in this study, but rather the mediating perception of technology attributes. Feelings of discomfort triggered by a lack of knowledge about the underlying data processes or uncertainty about privacy concerns seem to be promising factors explaining low continuance intention.

Third, current research is mainly limited to the characteristics of GenAI-based algorithms themselves (Nishant, Schneckenberg, & Ravishankar, 2023), ethics in GenAI use (Stahl & Eke, 2024), and the potential in adoption of GenAI applications. Thus, we place actual use and the user at the center of our discussion and focus on their usage behavior. Our results point to the complex interplay of motivational factors and the perceptions of technology characteristics that explain continuance intention among ChatGPT users. In addition, we have found renewed evidence for a link between ExM_{PU} and TeC_{PEOU} (P4), as well as the importance of TeC_{PEOU} and TeC_{NVL} (P2) in explaining usage behavior associated with IS adoption (Legris, Ingham, & Collerette, 2003; Wells et al., 2010). In this sense, previous research has suggested that the effect of TeC_{PEOU} wears off with continued use of an IS due to increasing familiarity with it (Yeh & Teng, 2012). The persistent influence of TeC_{PEOU} on ChatGPT usage observed in this study, even at the stage of continued use, may be due to its exceptional ease of use, which demands only little familiarization and differentiates it from other technologies that require extensive training.

Fourth, we provide a holistic view of IS usage behavior through a motivational lens. Previous research has shown the involvement of motivational factors in usage behavior (Bhattacherjee, 2001; Li et al., 2013; Venkatesh et al., 2003). We extend this knowledge by considering differentiated intrinsic and extrinsic motivational factors and technology characteristics in terms of TeC_{PEOU} and TeC_{NVL}. Our results show the necessity of distinguishing between different motivational factors by confirming a stronger influence of InM_{know} compared to $InM_{accomplish}$ (Li et al., 2013), which is generalizable to continuance intention (P3). Further research should now consider that this excess of intrinsic and extrinsic motivational factors over each other may be context-dependent as our study shows that, for example, $InM_{stimulation}$ has a variable influence on continuance intention with a more equal distribution between work and private contexts.

Fifth, we show equifinality in explaining usage behavior with motivational factors and technology characteristics, meaning that different configurations can equally explain the same outcome. This is important because the existing literature has focused on research models that assume linear and symmetric relationships (Li et al., 2013; Lowry et al., 2015). Our findings suggest that the interplay of motivational factors and technology characteristics leading to continuance intention among ChatGPT users is more complex than expected and that excluding of polyvalent multifactorial causation neglects crucial data. In this sense, we could show that different combinations of motivational factors and technology characteristics apply to different use cases and use contexts (P5). This has implications for future research models and theories, which need to consider equifinal paths to explain usage behavior, meaning that there is no homogeneous collective of users or that even the usage behavior of a single user is heterogeneous.

6.3. Implications for practice

The present study offers insights for distributors, developers, and users on how motivational factors and technology characteristics lead to high continuance intention for GenAI applications, exemplified with ChatGPT. Based on the analysis, we formulate practical suggestions in this section; see Table 16 for a summary.

6.3.1. Further improvement of usefulness and ease of use

Based on propositions P2 and P4, we recommend further improving the usefulness and ease of use of language-based GenAI applications such as ChatGPT. These two factors proved to be the most important in triggering continuance intention, independent of use context, but at the same time, the most relevant hindering factors are related to dissatisfaction with them. In particular, users would like to receive reliable, not superficial, and logical output that meets their quality expectations and is verifiable. In the same vein, users would like to be able to trace down the source of information, avoid obscure and incorrect databases, and be informed if copyrights could be harmed. Transparency about the data sources, including the possibility of verifying information within the application, would certainly increase satisfaction. Accordingly, the implementation of knowledge bases is recommended for GenAI applications like ChatGPT, both to provide appropriate information and to reassure users.

Table 16
Key examples of practical implications, organized by interest group.

Distributors	Developers	Users
• Ensure reliability, credibility, and traceability of information and address privacy concerns. • Promote diversity of use cases and encourage word-of-mouth recommendations.	• Enhance anthropomorphic qualities and incorporate gamified elements. • Provide the ability to set preferences or improve interactional learning. • Ensure usefulness and ease of use.	• Use GenAI applications for educational purposes. • Explore use cases across contexts.

This also applies to the domain of data governance, where privacy concerns are raised. Users mostly avoid providing personal information as input because they do not want it to be stored and reused for training the GenAI. They fear losing control over their informational property, which would make the GenAI application useless for the respective tasks. To account for this, the option to flag information that should not be reused for training purposes but should only remain in the control of the specific user, comparable to an anonymous mode, could meet the user's needs.

Another consequence of the dominant role of perceived usefulness and perceived ease of use is that these two factors together can even compensate for intrinsic amotivation, as the *extrinsically motivated* configuration implies. The equifinality of high continuance intention suggests that, in the work context, IT managers must deal with five combinations of motivational factors and technology characteristics that apply to different employees. Nevertheless, given the presence of perception of usefulness and ease of use, the chances are high that a particular user is willing to continue using the given IS.

6.3.2. The need and possibility to learn

Since the need to acquire knowledge is the most important intrinsic motivational factor in our study, and participants expressed concern about reduced learning using GenAI applications – as they take over certain tasks, and there is no need to become familiar with them –, one way to overcome this would be to encourage other forms of learning. One participant uses ChatGPT to learn a language by prompting for vocabulary lists and conjugation tables – here, the technology acts as a quizzing instance. Respondents also mentioned that ChatGPT helps them structure and organize information in specific areas of interest. If these use cases could be promoted more, users who are intrinsically motivated by knowledge acquisition and those who fear being "dumbed down" by GenAI could be addressed. The use of GenAI applications for educational purposes could therefore be threefold: freeing up capacity to acquire knowledge and develop new skills, structuring the information to be absorbed, and guiding the learning process with queries and corrections.

Staying in the realm of learning, participants complained about tedious interactions involving turning circles with outputs and prompts or the need for high specification of inputs to get useful results. It may be useful to build tutorials or guides for meaningful prompting into ChatGPT, as other text-based GenAI applications already do, to help users interact with the technology. This can reduce frustration and reignite intrinsic motivation to learn. In this sense, the instructiveness and anthropomorphic qualities of NLP-powered applications could be further enhanced by incorporating gamification elements – users could be rewarded with verbal praise for efficient prompting. There is a fine line between annoyance and engagement, but natural language simulation can potentially maintain this fourth wall of the user experience by not exposing this reinforcement as a mere algorithmic product. Furthermore, regarding data reliability, credibility, and traceability, there is a need to educate users, as they need to know that LLMs like ChatGPT only give the most probable answers, not necessarily the correct ones.

6.3.3. Differentiation between contexts and personalization

Building on proposition 5, another helpful feature might be to differentiate between contexts, such as work and private. Participants indicated that usefulness and ease of use are important regardless of context, but the use cases differ. At work, resource- and capacity-intensive tasks such as editing, writing, and processing text are most common, while private use is dominated by initiating thoughts or actions. In this sense, our findings indicate that the *comprehensively* *motivated* configuration – with an intrinsic focus – is mainly associated with private use cases. Thus, it might be desirable to have the option of different modes of use, one more concise and precise with a focus on efficiency and one with a more creative and innovative impulse.

Such preferences can be integrated with prompts, but general configuration options could be helpful. Interviewees said they liked the comprehensiveness of outputs and slower pace of text generation, while others complained about lengthy and slow answers. In this sense, some participants indicated a need for better personalization of the application, e.g. individual structuring of their search history besides the already existing possibility of opening new conversations. Then again, the application could learn more about preferences for specific response patterns from the interaction with the users, further enhancing the impression of natural communication.

6.3.4. Innovativeness and promotion of use cases

As indicated by participants, the influence of perceived novelty in the sense of use because of newness is of limited duration or unfolds mainly in the form of hype dynamics and social comparison. Nevertheless, innovativeness, defined here in terms of characteristics that distinguish a technology from others, can be a factor for adoption and, with continued usefulness, for continued use. For example, increasing the naturalistic appeal of the user interaction by further promoting spoken input and output can be perceived as novel but at the same time as useful and easy to use, thus maintaining user engagement as the use gains a quality of casualness.

New adopters may be attracted by this further reduced barrier to user interaction. However, according to the interviews, the use of applications such as ChatGPT is mainly limited by the innocence of possible use cases. Users may be willing to engage with these technologies, but many do not know why they should do so – this is the main reason for the observed gap between use in private and work contexts. In addition to promoting the various possible use cases and encouraging word-of-mouth recommendations – as socially connotated extrinsic motivation also proved to be influential – users could be tempted to further engage with ChatGPT through statements such as "You could also ask me […]" or "A similar task I could solve for you is […]". Again, user preference for such offers may be limited, so an option to turn off such recommendations should also be implemented.

6.4. Limitations and future research direction

The present study faces some limiting factors. First, we focus on continuance intention, which is likely but not certain to result in corresponding behavior. In the way we defined continuance intention, it represents the willingness to engage in continued use, not the actual use behavior itself. Therefore, we have accounted for a strong antecedent but cannot state a clear causal relationship between the motivational factors and technology characteristics considered and continued ChatGPT use. Likewise, statements about adoption, discontinuance intention, or corresponding behavior are impossible. Second, perceived usefulness emerged as the most relevant extrinsic motivational factor, but we only collected data on alternative factors in the qualitative study. There is no evidence that other extrinsic motivational factors could be more influential, but especially social aspects of peer comparison and word-of-mouth recommendation could be considered. Third, our results may still be limited by the novelty of ChatGPT. We found a difference in novelty perception between the two parts of our study. However, a strong effect of perceived ease of use still exists, so the future development of the influences of our examined factors on continuance intention needs to be considered. Especially since research on applications such as ChatGPT is still in its infancy compared to other applications in the field of GenAI, which are much more established among users. Fourth, because these two studies were tailored explicitly to ChatGPT and comparable text- respectively language-based GenAI applications, the generalizability to other technologies remains to be proven. Fifth, sampling for the quantitative study via an on-demand, self-service data collection platform combined with restrictive inclusion criteria resulted in a high-quality database for analysis but consequently a relatively high exclusion rate. For the qualitative study, social proximity sampling resulted in a highly educated sample. This has positive effects, such as the ability to conduct in-depth interviews due to informed knowledge and reflecting behavior, but it also limits generalizability. Sixth, the choice of fsQCA as a quantitative analysis that follows qualitative reasoning in combination with a subsequent purely qualitative analysis offers the possibility of comprehensive and relevance-oriented findings. However, it does not allow for common significance-based testing.

We now suggest four avenues for future research. First, we found that motivational factors and perceptions of technology characteristics related to innovation can explain high continuance intention among ChatGPT users but do not seem to explain the opposite. Further investigating factors that lead to low continuance intention or – as GenAI use may also fail in an initial phase (Reis, Maier, Mattke, Creutzenberg, & Weitzel, 2020) – even discontinuance intention, as well as the corresponding usage behavior, seems sensible in light of slightly declining user numbers (De Vynck, 2023). Different facets of satisfaction – with output and interaction – could be promising factors, as our findings suggest. Second, even the present sample, which is more likely to use GenAI applications given its ChatGPT use, clearly shows potential for expanding GenAI use (see Table 1), especially in private contexts (see Table 7). Therefore, it may be interesting to investigate the role of motivational factors in adopting GenAI applications to reach previous infrequent or non-users, which many participants reported from their social circle. Third, we investigated continuance intention among ChatGPT users from a motivational perspective. Meanwhile, questions have been raised about the trustworthiness of GenAI (Denning, 2023). Even in the survey, one participant expressed overt fear by stating, "AI terrifies me and I've only used Ghat GBT [sic] for harmless practical purposes like crafting a quick professional email", and an interviewee stated that they do not think that society is prepared for the influence of GenAI. Thus, research on issues such as trust, ethics, and privacy – as many participants called for more transparency – seems promising regarding GenAI usage behavior. Fourth, research could delve deeper into the area of anthropomorphism. Prior literature discussed the influence of anthropomorphism in the context of GenAI interaction (Mishra, Shukla, & Sharma, 2022) or even the possibility of developing romantic-like feelings for such an application (Song, Xu, & Zhao, 2022). In our study, we also noticed such tendencies, for example, calling unreliable and false output "hallucinations", referring to ChatGPT as "he" instead of "it/they", attributing thoughts, imaginative and creative capabilities, that would usually be considered human. More interesting, however, is the tendency of participants to present themselves as less human in their narrative identity during the interviews. While they ascribe human characteristics to ChatGPT or even consider it superior in certain domains, they doubt their own creativity and ability to learn or emphasize the need to personally contribute to the tasks solved with this application. We assume that users are challenged by their perception of human-like characteristics in technology, that they question the uniqueness of these human characteristics, and that they may tend to rate themselves lower in these domains. It is not only the perception of human-like features in technology that needs to be considered, but also how they affect the user's self-image and, as a result, their usage behavior.

7. Conclusions

Given the growing relevance of GenAI in all areas of life and the extraordinary growth in the number of ChatGPT users, we investigate the continuance intention of ChatGPT users. Drawing on well-established arguments from motivation theory and following a mixed-methods approach, we perform fsQCA on data from 279 ChatGPT users, and, building on this, we conduct semi-structured interviews with

15 participants. Our results reveal two necessary conditions – high perceived ease of use and high perceived novelty – of which perceived ease of use remains relevant after a longer period of use and five sufficient configurations leading to high continuance intention. Among the factors studied, we do not identify any necessary conditions or sufficient configurations that lead to low continuance intention, but we provide qualitative insights into hindering factors. Based on meta-inferences and propositions derived from them, we contribute to the literature on continuance intention, motivation in IS use, and ChatGPT. We reveal the complex interplay of motivational factors and technology characteristics in the context of individual ChatGPT use. As the innovative power of GenAI continues to redefine the world we live in, the age-old drivers of human behavior are still at work – the pursuit of knowledge, stimulation, usefulness, ease, and novelty are capable of determining whether we stay or stray from technologies such as ChatGPT.

CRediT authorship contribution statement

Vinzenz Wolf: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Christian Maier:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used *DeepL, DeepL Write,* and *Grammarly* for translation and to improve readability and language; *ChatGPT* was used to identify terms in the semantic proximity of code labels for their aggregation. After using these services, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table 17
List of survey items.

Construct	Items	Loadings	adopted from
$InM_{accomplish}$	1. I use ChatGPT because I feel a lot of personal satisfaction while mastering certain difficult skills.	.85	Li et al. (2013);Vallerand (1997);Vallerand et al. (1997);Van Yperen & Hagedoorn (2003)
	2. I use ChatGPT for the pleasure I feel while improving some of my weaknesses.	.85	
	3. I use ChatGPT for the satisfaction I experience while I am perfecting my use of it.	.88	
	4. I use ChatGPT for the satisfaction I feel while overcoming certain difficulties.	.86	
InM_{know}	1. I use ChatGPT for the pleasure it gives me to know more about it.	.82	Li et al. (2013);Vallerand (1997);Vallerand et al. (1997);Van Yperen & Hagedoorn (2003)
	2. I use ChatGPT for the pleasure I feel while learning new things.	.88	
	3. I use ChatGPT for the pleasure of developing new skills.	.87	
$InM_{stimulation}$	1. I find using ChatGPT to be enjoyable.	.94	Davis et al. (1992);Li et al. (2013)
	2. The actual process of using ChatGPT is pleasant.	.93	
	3. I have fun using ChatGPT.	.88	
ExM_{PU}	1. Using ChatGPT enables me to accomplish tasks more quickly.	.91	Davis (1989);Davis, Bagozzi, & Warshaw (1989);Hess et al. (2014); Li et al. (2013)
	2. Using ChatGPT improves my performance.	.92	
	3. Using ChatGPT increases my productivity.	.92	
	4. Using ChatGPT enhances my effectiveness.	.93	
	5. Using ChatGPT makes my life easier.	.87	
	6. Overall, I find ChatGPT useful.	.87	
TeC_{PEOU}	1. Learning to operate ChatGPT is easy for me.	.80	Davis et al. (1989);Hess et al. (2014);Li et al. (2013);Venkatesh et al. (2003)
	2. I find it easy to get ChatGPT to do what I want it to do.	.84	
	3. My interaction with ChatGPT is clear and understandable.	.87	
	4. ChatGPT is flexible to interact with.	.71	
	5. It would be easy for me to become skillful at using ChatGPT.	.78	
	6. Overall, I find ChatGPT easy to use.	.89	
TeC_{NVL}	1. I find using ChatGPT to be a novel experience.	.77	Wells et al. (2010)
	2. Using ChatGPT is new and refreshing.	.90	
	3. ChatGPT represents a neat and novel way of engaging with technology.	.88	
Continuance intention	1. I intend to continue using ChatGPT rather than discontinue its use.	.91	Bhattacherjee (2001);Mathieson (1991)
	2. My intentions are to continue using ChatGPT than use any alternative means.	.78	
	3. If I could, would like to discontinue my use of ChatGPT.	.81	

Table 18
Interview guide.

Introduction	How has the introduction of ChatGPT affected your life?
General usage behavior	When did you consciously start using AI?
	When did you consciously start using ChatGPT?
	How often do you use ChatGPT in your private life?
	How often do you use ChatGPT for work?
	Do you use any other AI applications?-Which ones privately?-Which ones at work?Which AI applications do you use most often?
Usage situations	In which situations do you use ChatGPT…
	– … privately?
	– … in a work context?
	How relevant is this for you in this situation?
	– "Accomplishment" = need to achieve something, to optimize yourself, to improve your handling of ChatGPT or to overcome obstacles.
	– "Knowledge" = need to learn more about ChatGPT, gain general knowledge or develop new skills.
	– "Stimulation" = using ChatGPT is enjoyable, pleasant or fun.
	– "Usefulness" = speed, performance, productivity, effectiveness, making everyday life easier.
	– "Ease of use" = Easy to learn, easy to instruct, clear and understandable interaction, flexible interaction, easy to master.
	– "Novelty" = New, refreshing, neat.
	Are there any other relevant factors?
	– … privately?
	– … in a work context?
	Are there any barriers or requirements to using ChatGPT in the work context?
	– e.g. expectations or regulation from superiors vs. privacy or ethical concerns
Continuance intention	Do you intend to continue using ChatGPT privately?
	– What factors are responsible for this?
	Do you intend to continue using ChatGPT in a work context?
	– What factors are responsible for this?
	Have you had any experiences with ChatGPT that have made you less likely to use it privately in the future?
	– What factors were responsible for this?
	Have you had any experiences with ChatGPT that have made you less likely to use it in a work context in the future?
	– What factors were responsible for this?
Extrinsic motivation	Definition: "Extrinsic motivation is triggered by external reinforcing factors, not by an activity itself."
	– To what extent is usefulness an extrinsic motivation?
	– How important is usefulness in your private life?
	– How important is usefulness in your work life?
	Can you think of any other extrinsic motivating factors for using ChatGPT?
	– … privately?
	– … in a work context?
	– Are these more or less important than usefulness?
Conclusion	To what extent is ChatGPT likely to influence your life in the future?

Note: The interviews were conducted in German; this is a literal translation of the interview guide.

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