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Chatbot interactions: How consumption values and disruptive situations influence customers' willingness to interact

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Abstract

Chatbots offer customers access to personalised services and reduce costs for organisations. While some customers initially resisted interacting with chatbots, the COVID-19 outbreak caused them to reconsider. Motivated by this observation, we explore how disruptive situations, such as the COVID-19 outbreak, stimulate customers' willingness to interact with chatbots. Drawing on the theory of consumption values, we employed interviews to identify emotional, epistemic, functional, and social values that potentially shape willingness to interact with chatbots. Findings point to six values and suggest that disruptive situations stimulate how the values influence WTI with chatbots. Following theoretical insights that values collectively contribute to behaviour, we set up a scenario-based study and employed a fuzzy set qualitative comparative analysis. We show that customers who experience all values are willing to interact with chatbots, and those who experience none are not, irrespective of disruptive situations. We show that disruptive situations stimulate the willingness to interact with chatbots among customers with configurations of values that would otherwise not have been sufficient. We complement the picture of relevant values for technology interaction by highlighting the epistemic value of curiosity as an important driver of willingness to interact with chatbots. In doing so, we offer a configurational perspective that explains how disruptive situations stimulate technology interaction.

KEYWORDS

chatbot, conversational agent, disruptive situation, fuzzy set qualitative comparative analysis (fsQCA), generative artificial intelligence (AI)

1 | INTRODUCTION

Many organisations offer customers information systems (IS) that simulate natural language interaction with a human advisor and serve as virtual assistants, that is, chatbots (Luo et al., 2019). Based on a predefined set of rules or generative artificial intelligence (Davymuka, 2023), chatbots provide customers with access to personalised services with a click of a button and benefit organisations by reducing customer interaction costs (Reddy, 2022). For example, chatbots allow customers to access financial services remotely (Dilmegani, 2023) and offer savings of up to US$ 7.3 billion by 2023 in the banking industry alone (Smith, 2019). Despite this, from a customer perspective, most customers preferred human-to-human interactions and resisted interacting with chatbots (Press, 2019). This preference changed with the COVID-19 outbreak, which disrupted the daily lives of many customers and sparked their willingness to interact (WTI) with chatbots (Magana, 2020). To fully leverage the potential of chatbots, organisations must understand the drivers, such as disruptive situations, that stimulate customers' WTI with chatbots.

Customers' WTI with chatbots, that is, their readiness to contact and respond to potential communication partners (Samochowiec & Florack, 2010) such as chatbots, is typically explained by customers' perceptions of the values offered by chatbots (see Table A1 in Appendix A). For example, customers have a WTI with chatbots when they experience emotional values, such as perceiving them as empathetic (Cheng et al., 2022), functional values, such as perceiving them as competent (Nguyen et al., 2022), and social values, such as perceiving them as socially attractive (Lee et al., 2022). However, disruptive situations, that is, discontinuities from the environment that require customers to adjust and have the potential to change their behaviour (Morgeson et al., 2015), may stimulate the relationship between values and WTI with chatbots, such that customers may have a WTI with chatbots despite not perceiving all values. The COVID-19 outbreak was such a disruptive situation for many customers in a way that they had to find new ways to interact with organisations, as human-to-human interaction was more difficult or not available due to infection risks (Magana, 2020).

We draw on the theory of consumption values (TCV) to link disruptive situations to values and WTI with chatbots, as it suggests that customers' behaviour results from their perceptions of a technology's emotional, epistemic, functional, and social values (Sheth et al., 1991). While not considered in prior chatbot literature, epistemic value is important for customer behaviour related to new experiences (Sheth et al., 1991), such as interacting with chatbots. Values' contributions to behaviour vary depending on whether customers are in an everyday life situation or a disruptive situation (Smith & Colgate, 2007). In everyday life situations, customers rely on rational considerations (Vázquez-Martínez et al., 2021), that is, they interact with a chatbot when perceiving ample values. In disruptive situations, their evaluation of whether chatbots offer ample values may change (Vázquez-Martínez et al., 2021).

While these situations may not change the assessed values of the chatbot (Sweeney & Soutar, 2001), they may cause customers to reconsider their assessment of whether existing values are ample enough to change their behaviour. As such, TCV provides a theoretical rationale for considering how disruptive situations stimulate the way values influence customers' WTI with chatbots.

We take these insights as an opportunity to integrate established value-based perspectives with a situational perspective (Burton-Jones et al., 2015) and theorise how disruptive situations stimulate the relationship between values and WTI with chatbots. We ask:

How does a disruptive situation stimulate the relationship between values and WTI with chatbots?

To answer this research question, we followed an abductive theory-building approach (Van Maanen et al., 2007). Drawing on TCV for an initial understanding of how emotional, epistemic, functional, and social values explain WTI with chatbots in disruptive situations, we conducted a two-step empirical approach in the illustrative context of banking. In the first step, we used a qualitative research design and conducted semi-structured interviews ($N = 51$) to identify six values that generally influence WTI with chatbots, irrespective of disruptive situations. In the second step, we integrated a scenario-based study with a quantitative study using fuzzy set qualitative comparative analysis (fsQCA) ($N = 153$) to reveal how a disruptive situation stimulates the relationship between combinations of the identified values, that is, configurations, and WTI with chatbots. Results reveal three configurations stimulated by the disruptive situation (i.e., disruption-stimulated) and one configuration not affected by the disruptive situation (i.e., disruption-robust) that explain WTI with chatbots. Findings reveal a disruption-robust configuration that describes customers with no WTI with chatbots. Based on a dialogue between our findings and TCV, we developed propositions for the theoretical mechanisms across the sufficient configurations and the theoretical mechanisms within the sufficient configurations.

We contribute to the chatbot and TCV literature. Taking a situational and configurational perspective, we show that values explain WTI and no WTI with chatbots symmetrically, that is, customers who experience all values have a WTI with chatbots and those who experience none have no WTI with chatbots, irrespective of whether they experience a disruptive situation. We show that disruptive situations stimulate WTI with chatbots so that customers with different value configurations that would not have been sufficient otherwise have a WTI with chatbots. This way, we extend TCV research by going beyond established value-based explanations and probing disruptive situations as a boundary condition for customers' WTI with chatbots. By integrating the chatbot literature with TCV, we add epistemic value as an important driver of WTI with chatbots to the known emotional, functional, and social values.

2 | CUSTOMER INTERACTIONS WITH CHATBOTS

In recent years, the literature on chatbots has grown (Diederich et al., 2022). The chatbot literature studies diverse topics, including customers' WTI with chatbots in terms of their reliance on the chatbot (Cheng et al., 2022), engagement (Chandra et al., 2022), and use (Gnewuch et al., 2022) (see Table A1 in Appendix A). While the studies draw on various theoretical lenses, such as cognitive fit theory (Chen et al., 2021) and social presence theory (Schuetzler et al., 2020), at their core, they largely rely on customers' perceptions of chatbots' *values* to explain WTI with chatbots (see Table A1 in Appendix A).

The literature identifies emotional (Huang & Lee, 2022), functional (Shin et al., 2022), and social values (Schanke et al., 2021). Emotional values such as perceived empathy and emotional arousal promote customer use of chatbots (Cheng et al., 2022; Huang & Lee, 2022). Functional values such as perceived task-solving competence and perceived personalization of responses increase customers' trust in chatbots and their attachment to chatbots (Jiang et al., 2023; Lee et al., 2022). Social values, such as perceiving chatbots as human-like social actors, that is, perceived anthropomorphism and perceived social presence, increase customer satisfaction and use of chatbots (Gnewuch et al., 2022; Konya-Baumbach et al., 2023). Epistemic values, such as curiosity (Agarwal & Karahanna, 2000), are not considered in extant chatbot literature.

All identified values explain customers' WTI with chatbots in their everyday lives. Yet, customers occasionally face disruptive situations that require them to readjust and can stimulate their behaviour beyond values (Maier et al., 2024). To integrate disruptive situations into explanations of WTI with chatbots, we leverage the TCV.

3 | THEORETICAL BACKGROUND

3.1 | Theory of consumption values

We draw on three key insights of TCV to theorise how disruptive situations, such as the COVID-19 outbreak, stimulate WTI with chatbots.

The first key insight suggests that customers' perceptions about the values of a technology explain their behaviour (Sheth et al., 1991). It posits that different values influence behaviour, that is, emotional, epistemic, functional, and social values (Sweeney & Soutar, 2001) (see Table 1). Rather than offering predefined values, TCV suggests that researchers identify and categorise values along those value types (Mäntymäki et al., 2020). This is important because the values and their influence on behaviour vary depending on the context (Hong et al., 2014).

The second key insight of TCV postulates that values are situational (Smith & Colgate, 2007), suggesting that behaviour depends on customers' perception of the specific situation in which the value evaluation occurs (Sweeney & Soutar, 2001; Zeithaml et al., 2020). Research in the same line of argumentation suggests that customers' perceptions of situations influence their behaviour (Belk, 1975). In their everyday life, customers rely on their rational considerations (Vázquez-Martínez et al., 2021). In other words, they behave in a certain way, such as buying a specific product or interacting with a specific technology, when they perceive ample values (Sheth et al., 1991). The evaluation of whether values are ample changes when customers perceive a disruptive situation, such as the COVID-19 outbreak (Vázquez-Martínez et al., 2021). Disruptive situations describe discontinuities in the environment that require customers to readjust and have the potential to change their behaviour (Morgeson et al., 2015). When customers are in a disruptive situation that a product or technology can support, they reevaluate whether its values are ample for a behaviour (Vázquez-Martínez et al., 2021), that is, they lower their mental threshold at which the perceived values lead to a behaviour. For example, studies show that disruptive situations such as the birth of a child or developing health problems make grocery shopping more difficult, leading some customers to start shopping online (Hand et al., 2009). Recognising that the way values influence behaviour depends on customers' perception of the specific situation allows us to probe how disruptive situations stimulate the influence of values on WTI with chatbots.

The third key insight of TCV emphasises that behaviour is a function of multiple values (Sheth et al., 1991), suggesting that the values relevant to a particular context do not contribute to behaviour in isolation (Zeithaml et al., 2020). Rather, the multiple values interrelate and are evaluated jointly by customers (Sweeney & Soutar, 2001), suggesting that combinations of different values, so-called *configurations*, must be considered to comprehensively explain behaviour (Gonçalves et al., 2016). Research extends this with the notion that values are

TABLE 1 Types of values.

Value types	Definition (Sheth et al., 1991)
Emotional	The perceived utility acquired from an alternative's capacity to arouse feelings or affective states.
Epistemic	The perceived utility acquired from an alternative's capacity to arouse curiosity, provide novelty, or satisfy a desire for knowledge.
Functional	The perceived utility acquired from an alternative's capacity for utilitarian or physical performance.
Social	The perceived utility acquired from an alternative's association with one or more specific groups.

personal (Holbrook, 1996) and that different customers may weigh the relevance of values for a behaviour differently (Sweeney & Soutar, 2001), suggesting that customers have different reasons for their behaviour. Taken together, TCV suggests that customers follow different reasoning for their behaviour, and each reasoning consists of multiple interacting values.

IS research employs TCV to study customers' technology interactions in contexts such as digital content services (Mäntymäki et al., 2020), hedonic digital artefacts (Turel et al., 2010), and social networking sites (Kim et al., 2011). The findings of these studies explain how values sensitive to certain technologies influence behaviour and provide general explanations independent of the disruptive situations (see Table A2 in Appendix A).

While IS research draws on the first key insight of TCV to explain technology interaction in different contexts based on emotional, epistemic, functional, and social values, there are two directions for leveraging the second and third key insights to explain how disruptive situations stimulate WTI with chatbots (see Table 2). The second key insight of TCV suggests that values contribute differently to behaviour in specific situations (Sweeney & Soutar, 2001), that is, how values lead to behaviour differs in disruptive situations (Vázquez-Martínez et al., 2021). This insight directs attention to how customers' perceptions of a specific situation, that is, disruptive situation versus no disruptive situation, stimulate the relationship between values and technology interaction. Such a situational perspective is particularly relevant for understanding why and how disruptive situations stimulate WTI with chatbots.

The third key insight of TCV highlights that values are interrelated and collectively contribute to behaviour (Zeithaml et al., 2020) and that customers may differ in their reasoning for behaviour (Sweeney & Soutar, 2001). Related IS literature explains how the values uniquely contribute to behaviours such as technology use (Yang & Lin, 2017; Zhu et al., 2023). Existing explanations that follow—from a methodological point of view—linear logic do not consider equifinality and conjunctural causation (Mattke et al., 2021), that is, different configurations of values, rather than isolated values, form behaviour. We take this as an opportunity to propose a configurational perspective, considering that different configurations of multiple emotional, epistemic, functional, and social values explain WTI.

3.2 | Toward a situational and configurational perspective on WTI with chatbots

Some IS research has linked the context to specific technology-related situations, showing that technology breakdowns (Ortiz de Guinea & Webster, 2013) and security threats (Liang et al., 2019) affect how customers interact

TABLE 2 Leveraging the key insights of TCV to explain WTI with chatbots.

Key insight of TCV	Application in IS research using TCV	Implications for this study
1. Emotional, epistemic, functional, and social values influence behaviour (Sheth et al., 1991).	*Fully used*. IS research identifies emotional, epistemic, functional, and social values in different contexts (see Table A2).	Emotional, epistemic, functional, and social values in the context of chatbots need to be identified to explain WTI with chatbots.
2. Values contribute differently to behaviour based on customers' perceptions of specific situations (Belk, 1975; Zeithaml et al., 2020).	*Not used*. IS research does not consider customers' perceptions of specific situations (e.g., disruptive situation vs. no disruptive situation).	Customers' perceptions of disruptive situations stimulate how the different values influence WTI with chatbots.
3. Values collectively contribute to behaviour, and different customers can weigh the relevance of values for a behaviour differently (Holbrook, 1996; Sweeney & Soutar, 2001).	*Not used*. IS research focuses on how isolated values influence behaviour, not considering that values influence behaviour in configurations and that customers might differ in their reasoning.	Customers follow different rationales for their WTI with chatbots, each consisting of multiple values.

with technology. For example, data breaches may cause customers to switch to an alternative technology (Nikkhah & Grover, 2022). Even when technology interaction research examines specific situations, it draws attention to technology-related situations and their behavioural consequences. Despite these insights, other IS research contexts suggest that disruptive situations beyond specific technology-related situations can influence behaviour. For example, in the context of open-source communities, disruptive situations such as the COVID-19 outbreak can cause users to increase their contributions to projects (Malgonde et al., 2023). Similarly, there are indications that such disruptive situations can cause customers to increase their use of streaming services and collaboration software (Meier et al., 2022). Such insights suggest an opportunity to study if and how disruptive situations, such as the COVID-19 outbreak, influence customers' technology interactions, such as their WTI with chatbots.

To understand how disruptive situations stimulate WTI with chatbots, we turn to management research, showing that situations influence behaviour based on individuals' perceptions of their disruption (Maier et al., 2021). Individuals differ in their assessment of the disruptiveness of a situation (Kammeyer-Mueller et al., 2005; Pleskac et al., 2011), suggesting that some customers will evaluate a particular situation as highly disruptive, that is, a *disruptive situation*, while others will not. Disruptive situations interfere with individuals' status quo (Holtom et al., 2005) and potentially influence their behaviour in a specific context, while non-disruptive situations do not have such power.

For example, in the banking context, customers were asked to change their behaviour when COVID-19 broke out, that is, to stop going to the actual bank. For some customers, this change significantly altered how they managed their finances (Bellens, 2020). They limited their personal contact with other people and their interactions with their human bank advisor. They looked for new ways to interact with their bank to manage their finances (i.e., a disruptive situation for handling financial matters), such as considering interacting with a chatbot instead of their human bank advisor. Other customers were less affected by this situation because they were used to handling their financial matters without human assistance (i.e., no disruptive situation for handling financial matters). Since customers prefer interacting with chatbots over human advisors when seeking fact-based and logical advice (Longoni & Cian, 2022), a disruptive situation incentivised many customers to deviate from their established behaviour and shift to interacting with chatbots to handle financial matters.

Rooted in TCV and the related literature, we propose that configurations of emotional, epistemic, functional, and social values explain WTI with chatbots stimulated by disruptive situations. To reflect the configurational perspective, we consider that configurations may include present and absent values and that the configurations giving rise to no WTI with chatbots may not be the opposite of the configurations giving rise to WTI with chatbots (see Figure 1).

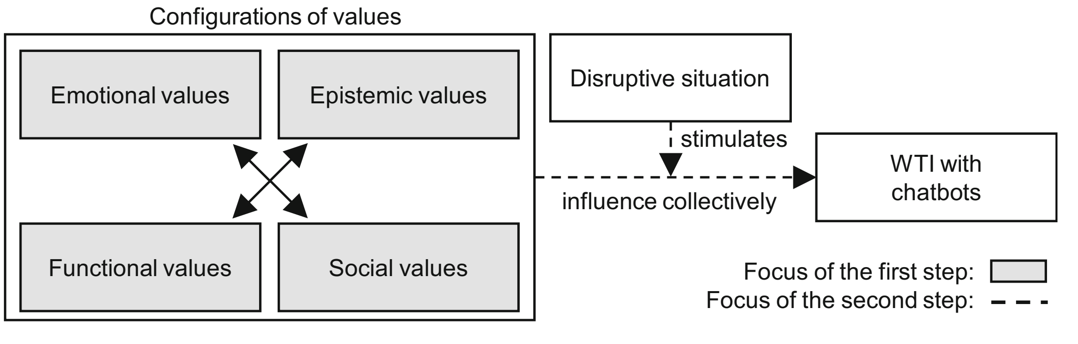

FIGURE 1 Research approach.

4 | METHODOLOGY

We conducted a two-step empirical approach to examine how disruptive situations stimulate WTI with chatbots. Since practical data suggests that when COVID-19 broke out, bank customers' interactions with chatbots increased (Magana, 2020), we consider banking an appropriate illustrative context to probe how configurations influence WTI with chatbots stimulated by a disruptive situation. Banks typically provide chatbots to their customers free of charge through their websites or mobile applications (Peck, 2022). Chatbots provide customers natural language access to financial services using voice or text (Dilmegani, 2023). For example, customers request assistance with financial transactions, ask chatbots for information about bank accounts or credit cards, or ask frequently asked questions (Bika, 2020). Chatbots also detect unusual transactions and provide insight into money spending patterns (Franco, 2021).

In the first step, we used a qualitative approach to identify values that generally explain WTI with chatbots according to the four value types of TCV in this illustrative context. In the second step, we used the identified values to conduct a scenario-based study to contrast how configurations of the values influence WTI with chatbots based on whether customers perceived a disruptive situation.

4.1 | First step: Values influence WTI with chatbots

4.1.1 | Data collection

We purposefully sought out and interviewed bank customers whose banks offered chatbots to gain insight into the values that influence customers' interactions in this illustrative context. We approached a snowballing sample by identifying potential participants through the authors' circles of acquaintances and using the snowballing technique to identify additional participants matching the eligibility criteria (Myers & Newman, 2007). The semi-structured interviews were guided by an iteratively developed set of questions (Myers & Newman, 2007; Schultze & Avital, 2011) (see Table B1 in Appendix B). We asked participants about the reasons they interacted with chatbots. To elicit detailed information, we used the "laddering" technique to repeatedly ask 'why' and 'why not' questions to get to the bottom of their reasons (Schultze & Avital, 2011). We conducted interviews until we reached saturation and no new concepts were identified. In total, we interviewed 51 customers with access to chatbots from their banks, which is a good sample size for qualitative studies (Collins et al., 2006). We recorded and transcribed the interviews with the participants' permission for the qualitative analysis. Each interview lasted approximately ten to 25 min. The participants' demographics reflect that largely younger customers interact with chatbots (see Table 3) (Cheng et al., 2022).

4.1.2 | Data analysis and validation

We followed an established coding scheme (Myers, 2019). We identified statements describing participants' perceptions of a chatbot's values that lead them to interact with it. We then used descriptive and subsequently interpretive coding to group similar statements (Myers, 2019) and identify different values influencing WTI with chatbots. For example, we coded this statement with the descriptive code *Chatbot is understanding*: "A chatbot is simply more understanding. It is more forgiving and not immediately annoyed when you don't understand something and have to ask again". We then used interpretive coding to group similar descriptive codes. For example, we grouped the descriptive codes *Chatbot is understanding* and *Chatbot is friendly* to the interpretive code *perceived empathy*. We validated the qualitative findings and determined the design validity, analytical validity, and inferential validity (see Table B3 in Appendix B).

TABLE 3 Demographics of the 51 participants.

Age (in percent, Mean: 29.04; SD: 9.55)		Biological sex (in percent)		Education (in percent)		Used functionalities (in percent)	
<26 years	43.14	Male	56.86	High school	33.33	Gathering general information	64.71
26–30 years	35.30	Female	43.14	Bachelor's degree	27.45	Gathering sensitive information	47.06
31–35 years	7.84			Master's degree	29.41	Financial transactions	45.10
36–40 years	5.88			Other	9.81	Administrative tasks	31.37
>40 years	7.84					Fraud detection	11.76

Note: "Gathering general information" includes asking frequently asked questions or getting information about a bank's products. "Gathering sensitive information" includes checking the bank account balance or recent credit card transactions. "Financial transactions" include making money transfers. "Administrative tasks" include changing a credit card limit or locking a credit card. "Fraud detection" includes getting notified about unusual transactions.

4.1.3 | Results

We identified six values relevant to WTI with chatbots: *perceived empathy*, *curiosity*, *perceived personalization*, *perceived benefit*, *perceived objectivity*, and *perceived anthropomorphism*. While the values of perceived empathy (Cheng et al., 2022), perceived personalization (Rhee & Choi, 2020), perceived benefit (Jiang et al., 2023), and perceived anthropomorphism (Go & Sundar, 2019) are well-known in chatbot literature, we identified curiosity and perceived objectivity as additional drivers of customers' WTI with chatbots. We draw on broader IS research to define curiosity (Agarwal & Karahanna, 2000) and on management research to define perceived objectivity (Uhlmann & Cohen, 2007) (see Table 4).

Consistent with TCV and IS research (Mäntymäki et al., 2020), we enriched our qualitative findings with previous literature to categorise the identified values as *emotional*, *epistemic*, *functional*, and *social values* (see Table 4). To assess the validity of the categorization, we used a Q-sorting approach. Since all categorised values exceeded a hit rate of 61 percent (see Appendix B), we conclude that the assignment of the identified values to *emotional*, *epistemic*, *functional*, and *social values* is valid.

The interviews supported the practical evidence that a disruptive situation stimulates how the values influence WTI with chatbots. While some customers perceived the COVID-19 outbreak as a disruptive situation for handling financial matters, others did not, which is reflected in the quotes from the interviews (see Table 5).

4.2 | Second step: Configurations of values influence WTI with chatbots stimulated by disruptive situations

We draw on qualitative insights to examine how the identified values influence WTI with chatbots stimulated by the disruptive situation. We used fsQCA to analyse data from a scenario-based study.

4.2.1 | Procedure of the scenario-based study

We created two scenarios. Scenario A described the COVID-19 outbreak as a disruptive situation for handling financial matters. Scenario B described it as no disruptive situation for handling financial matters (see Appendix C). We aligned our design with previous scenario-based studies (D'Arcy et al., 2014). Participants were randomly exposed to one of the two scenarios and then asked to complete a survey. To avoid demand, priming, and ordering effects, participants were unaware of the study's purpose, and each participant took part in only one of the scenarios.

TABLE 4 Identified values.

Value type	Identified value	Definition	Evidence from interviews	Explanation based on extant literature
Emotional	Perceived empathy (adapted from Cheng et al., 2022)	The degree to which customers believe that a chatbot can identify, understand, and react to their thoughts, feelings, behaviour, and experiences.	"A chatbot is simply more understanding. It is more forgiving and not immediately annoyed when you don't understand something and have to ask again". "When I don't feel like talking to bank advisors, the chatbot is much more pleasant. It's always friendly, can't be in a bad mood, and you don't get a snotty answer".	Empathy describes the emotional response to another person's emotional state (Eisenberg & Strayer, 1987). While empathy is known as an essential factor in establishing and maintaining interpersonal relationships between customers and human advisors (Wieseke et al., 2012), recent research shows that the degree to which customers believe that a chatbot possesses empathy also plays an important role in chatbot-human interaction (Cheng et al., 2022). Integrating literature postulating that empathy depicts an emotional reaction with TCV, we suggest that customers' perception of a chatbot's empathy in response to their own emotional state represents an emotional value for customers.
Epistemic	Curiosity (adapted from Agarwal & Karahanna, 2000)	The degree to which the interaction with a chatbot invokes customers' excitement about available possibilities.	"Out of pure curiosity. I wanted to see how it works, if it's like a real conversation, and if I get the right answers". "I was curious. So what functions it would have, what questions you could ask, for example, to open a new account. That is	When customers perceive a gap in information in a specific context (Loewenstein, 1994), it arouses their sensory and cognitive curiosity (Malone, 1981). Curiosity contributes to customers' technology interaction (Agarwal

(Continues)

TABLE 4 (Continued)

Value type	Identified value	Definition	Evidence from interviews	Explanation based on extant literature
			quite exciting for me".	& Karahanna, 2000). In line with TCV (Sheth et al., 1991), we suggest that curiosity depicts an epistemic value.
Functional	Perceived personalization (adapted from Gu et al., 2020)	The degree to which customers believe that a chatbot understands their specific preferences and then offers personalised services that address their needs.	"It's also good that the chatbot knows and takes into account my personal circumstances". "I also like the fact that I get answers that are tailored to me. No generic nonsense like look at the FAQs, but actual information about my bank accounts and my financial situation".	Personalization describes the degree of a technology's adaptation to customers' needs (Sundar & Marathe, 2010). It describes the experiences customers have with tailoring technology to meet their specific needs (Lee & Lin, 2005). Following research that postulates that personalization allows to adapt technologies to customers' changing needs and so keep them relevant to customers (Wang et al., 2017), we categorise customers' perception of a chatbot's personalization as functional value.
	Perceived benefit (adapted from Kim et al., 2009)	The degree to which customers believe that a chatbot is valuable for performing a specific task, for example, handling financial matters.	"It simply takes less time, because you don't have to go to the bank or wait for hours on the telephone hotline". "You get more precise help, because chatbots can answer the questions you have quite well and you are not forwarded 40 times to people who can answer your question. It makes	TCV explains that customers are interested in technologies with functional and utilitarian attributes relevant to completing necessary tasks (Sheth et al., 1991). This view is supported in chatbot research, which shows customers interact with chatbots when they perceive them as beneficial for a

TABLE 4 (Continued)

Value type	Identified value	Definition	Evidence from interviews	Explanation based on extant literature
			everything faster and easier."	specific task (Jiang et al., 2023), for example, when chatbots increase their productivity in handling financial matters. We accordingly categorise perceived benefit as functional value.
	Perceived objectivity (adapted from Uhlmann & Cohen, 2007)	The degree to which customers believe that a chatbot performs tasks and gives advice fact-based and impartially.	"Another advantage is that you don't have to ask bank advisors who might want to talk you into something. You don't know what they actually want, if they really want to advise you well or if they are just out for a commission. I believe that the chatbot sees things more objectively and not as subjectively as a human". "I think that a chatbot informs me more objectively than a human bank advisor. That it advises me fact-based and without ulterior motives".	Marketing research suggests that customers who perceive an advertisement as objective are more likely to respond positively (Darley & Smith, 1993). Financial research underlines this, showing that some customers are sceptical about the potentially biased advice they receive from human bank advisors (Berg, 2008). Following indications that customers are more likely to respond with favourable behaviour when they perceive advice as fact-based and impartial, we suggest that customers appreciate the perception that a chatbot offers objective advice as a functional value.
Social	Perceived anthropomorphism (adapted from Epley et al., 2007)	The degree to which customers attribute human characteristics to a chatbot and perceive it as a social actor.	"The chatbot is actually quite nice and friendly. Talking to it is like talking to a bank employee who has been sitting there for 30 years and is not motivated, only better".	Customers tend to attribute non-human entities like chatbots with human-like characteristics (Ochmann et al., 2024; Schuetzler et al., 2020), especially when they

(Continues)

TABLE 4 (Continued)

Value type	Identified value	Definition	Evidence from interviews	Explanation based on extant literature
			"I find it quite funny that you interact with chatbots like with people, even though they are machines. Chatbots are always friendly, so when you give them voice commands, they say that they didn't understand the command and that you should please repeat it, which is quite cute".	lack a sense of social connection to other humans (Epley et al., 2007). They apply social norms to the technology they perceive as anthropomorphic and perceive such technology as a social actor (Nass & Moon, 2000), which changes how they interact with them (Park et al., 2021). Given that individuals draw from the perception of anthropomorphism to substitute social connections with humans (Epley et al., 2007), we categorise perceived anthropomorphism as social value.

4.2.2 | Data collection

Consistent with IS research (Yazdanmehr et al., 2020), we used Amazon Mechanical Turk (MTurk) to recruit participants whose banks offer a chatbot. We followed guidelines for data collection using MTurk to obtain reliable and valid data (Lowry et al., 2016). We used MTurk filters to invite participants who resided in the United States. We excluded MTurk workers who frequently completed tasks in very short timeframes based on their approval rate of previous tasks and the overall number of approved tasks. To motivate participants to provide accurate responses, we included attention checks such as "Please choose 'Disagree'" in our survey. To ensure participants were familiar with chatbots and that their bank offered a chatbot, we included screening questions such as "Are you familiar with banking chatbots?" and "Does your bank offer a banking chatbot?" (see Table C1 in Appendix C). We only allowed participants to proceed with the survey when they answered all screening questions correctly. We ensured that the participants read and understood the scenarios by filtering for participants who reported the COVID-19 outbreak as a disruptive situation for handling financial matters in Scenario A and participants who did not report it as a disruptive situation for handling financial matters in Scenario B based on established measures (Morgeson, 2005) (see Table C2 in Appendix C). This ensured a successful manipulation of the disruptive situation for handling financial matters. We compensated participants above the US minimum wage.

175 participants passed our screening questions and attention checks. The average time to complete the survey was 8.68 min, so we removed 21 participants who completed the survey in less than 3 min. We deleted one participant because of not answering more than two questions. Our final sample consisted of 153 participants, 76 of whom

TABLE 5 Disruptive situation.

Situation	Evidence from interviews
A disruptive situation for handling financial matters.	"Thanks to COVID-19, waiting times at banks have skyrocketed. And, of course, it's also nice to be able to do things with a chatbot in such a situation without having to go see the bank advisor in person".
No disruptive situation for handling financial matters.	"I was not really affected by the outbreak of COVID-19. It was probably more relevant for people who regularly consult their human bank advisor".

were exposed to Scenario A and 77 of whom where exposed to Scenario B. We examined seven conditions, that is, six values and a disruptive situation, with 153 observations. With this, we follow the recommendations for large-N QCA to include more than 50 observations and not more than eight conditions (Greckhamer et al., 2013; Mithas et al., 2022). Our sample also includes more than five observations for every condition, which is consistent with recent methodological suggestions for QCA (Mattke et al., 2022). The data is available at the Open Science Foundation.[1] We report the demographics in Table 6.

4.2.3 | Measures and measurement model

We adapted the measures to the banking context by referring to the respective chatbots wherever possible (see Table C2 in Appendix C). We measured all items using a seven-point Likert scale from one ("Strongly disagree") to seven ("Strongly agree").

We evaluated the adapted measures' indicator reliability, construct reliability, and discriminant validity (Mattke et al., 2021). We dropped one item of *perceived empathy* due to its low loading. We provide an overview of the items and their loadings in Table C2 in Appendix C. We state *indicator reliability*, as all remaining items exceed the threshold of 0.707 (Carmines & Zeller, 2008). As the composite reliability of all measures is greater than 0.70 and the average variance extracted (AVE) of all measures is greater than 0.50 (see Table 7), we are confident about *construct reliability*. The square root of each measure's AVE is greater than the corresponding construct correlations (see Table 7), suggesting *discriminant validity* (Fornell & Larcker, 1981). Examining the cross loadings, we find that the loadings of each item are the highest for the corresponding construct (see Table C3 in Appendix C), indicating discriminant validity (Chin, 1998). Applying the heterotrait-monotrait (HTMT) ratio test, we find that the highest value is 0.84, which is below the $HTMT_{0.85}$ threshold (Henseler et al., 2015), allowing us to conclude discriminant validity. We are confident that our measures are reliable, discriminant, and convergent.

4.2.4 | Data analysis using fsQCA

We applied a fsQCA to study how the values influence WTI with chatbots. This configurational approach enables us to analyse how configurations of values influence the outcome of WTI with chatbots stimulated by the disruptive situation. We examined configurations of the six identified values *perceived empathy*, *curiosity*, *perceived personalization*, *perceived benefit*, *perceived objectivity*, and *perceived anthropomorphism*. We also included a *disruptive situation*, allowing us to separate the solutions for WTI and no WTI with chatbots based on the presence and absence of the disruptive situation. We include the values and the disruptive situation in the fsQCA as conditions. A condition refers to a set membership of a variable, and its value expresses the extent to which a condition is fully in a set

[1]Chatbot interactions: How consumption values and disruptive situations influence cCustomers' willingness to interact. https://doi.org/10.17605/OSF.IO/FK3YQ.

TABLE 6 Demographics of the 153 participants.

Age (in percent, Mean: 34.92; SD: 10.10)		Biological sex (in percent)		Education (in percent)	
<26 years	21.57	Male	44.44	High school	9.81
26–30 years	18.95	Female	54.90	Bachelor's degree	62.09
31–35 years	18.30	Other	0.66	Master's degree	27.45
36–40 years	20.26			Other	0.65
>40 years	20.92				

(i.e., present) or fully out of a set (i.e., absent) (Mattke et al., 2021). As outcomes, we investigated WTI with chatbots and no WTI with chatbots. In each analysis, we first analysed necessary conditions, which describe values that must be present or absent for customers to show WTI or no WTI with chatbots. We then analysed for sufficient configurations, which describe configurations of values that result in either WTI or no WTI with chatbots.

fsQCA relies on set memberships. Conditions and outcomes are represented by fuzzy set memberships that range from zero to one. While a fuzzy set membership of zero indicates that a customer does not perceive a particular value, a fuzzy set membership of one indicates that a customer does perceive the value. For example, a membership of zero for perceived benefit indicates that a customer does not perceive a chatbot as beneficial, a membership of 0.30 indicates that a customer tends not to perceive it as beneficial, a membership of 0.70 indicates that a customer tends to perceive it as beneficial, and a membership of one shows that a customer perceives it as beneficial. Appendix C describes the calibration, analysis for necessary conditions, and analysis for sufficient configurations of fsQCA. We validate the quantitative findings and report the design validity, measurement validity, and inferential validity (see Table C6 in Appendix C).

4.2.5 | Results

The analysis for necessary conditions revealed that the emotional value of *perceived empathy* (consistency = 0.95, coverage = 0.80, relevance of necessity = 0.62) and the functional value of *perceived objectivity* (consistency = 0.91, coverage = 0.80, relevance of necessity = 0.66) exceed the necessary condition thresholds for WTI with chatbots. Despite passing the necessary condition thresholds, perceived objectivity is not included in all sufficient configurations for WTI with chatbots. Since perceived objectivity as a necessary condition conflicts with the sufficient configurations (Mattke et al., 2021) and its explanatory power measured by the Banzhaf index is lower or equal than most other values (see Table C4 in Appendix C) (Haake & Schneider, 2023), we decided not to include it as a necessary condition. The analysis for sufficient configurations revealed four sufficient configurations for WTI with chatbots and one for no WTI with chatbots (see Figure 2). The identified sufficient configurations reflect the complex solution that matches the intermediate solution since we did not draw on theoretical insights to employ counterfactuals. By using each possible counterfactual, we identified the parsimonious solutions (please see Figure C1 in Appendix C).

We combined the intermediate solution, which also reflects the complex solution, and the parsimonious solution to identify core and peripheral conditions. Core conditions are conditions with a strong causal relationship with an outcome within a sufficient configuration, and peripheral conditions are conditions with a weaker causal relationship with an outcome within a sufficient configuration (see Appendix C). Because we did not theorise about a distinction between core and peripheral conditions 'a priori', we report them without distinguishing between them in the theoretical interpretations for the sake of transparency (Dwivedi et al., 2018).

To explain how a disruptive situation stimulates WTI with chatbots, we follow previous configurational IS research (Lee et al., 2019; Park et al., 2017) to separate the sufficient configurations based on the disruptive situation. This allowed us to study how a present or absent disruptive situation stimulates the sufficient configurations

TABLE 7 Descriptive statistics and discriminant validity.

		M	SD	CR	CA	AVE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Perceived empathy	4.96	1.12	0.87	0.78	0.69	0.83							
(2)	Curiosity	4.54	1.35	0.93	0.89	0.82	0.66	0.91						
(3)	Perceived personalization	4.79	1.14	0.90	0.84	0.76	0.68	0.56	0.87					
(4)	Perceived benefit	5.10	1.07	0.91	0.88	0.68	0.62	0.59	0.64	0.82				
(5)	Perceived objectivity	4.79	1.04	0.91	0.88	0.59	0.58	0.45	0.43	0.51	0.77			
(6)	Perceived anthropomorphism	3.78	1.75	0.96	0.95	0.84	0.49	0.58	0.52	0.29	0.35	0.92		
(7)	Disruptive situation	3.98	1.82	0.93	0.90	0.82	0.16	0.17	0.15	0.13	0.03	0.17	0.90	
(8)	WTI with chatbots	4.47	1.44	0.94	0.92	0.80	0.65	0.64	0.49	0.55	0.52	0.56	0.22	0.89

Note: The table displays the bivariate correlations between the constructs, and the square root of the AVE is listed on the diagonal of bivariate correlations.
Abbreviations: AVE, average variance extracted; CA, Cronbach's α; CR, composite reliability; M, mean; SD, standard deviation.

that lead to WTI and no WTI with chatbots. We revealed three sufficient configurations that explain WTI with chatbots when customers experience a disruptive situation (*sensitive customer*, *pragmatic customer*, *apathetic customer*), that is, disruption-stimulated configurations, and one sufficient configuration that explains WTI with chatbots irrespective of whether a customer experiences a disruptive situation (*fastidious customer*), that is, disruption-robust configuration. Similarly, we identified one disruption-robust configuration for no WTI with chatbots (*rejecting customer*). We present a graphical representation of our results in Figure 2.

We evaluated the quality of our solutions based on consistency, which describes the extent to which a solution explains an outcome (Schneider & Wagemann, 2010), and coverage, which represents the proportion of observations covered by a solution (Ragin, 2006). For WTI with chatbots, the solution consistency is 0.92, and the solution coverage is 0.74. The solution consistency for no WTI with chatbots is 0.99, and the solution coverage is 0.35 (see Figure 2).

The first sufficient configuration for WTI with chatbots, which we labelled the *sensitive customer*, depicts customers who experienced a disruptive situation as a core condition. They experienced a configuration of values, including the epistemic value of curiosity and the social value of perceived anthropomorphism as core conditions, and the emotional value of perceived empathy and the functional values of perceived personalization and perceived benefit as peripheral conditions. The functional value of perceived objectivity is irrelevant for *sensitive customers*.

The second sufficient configuration for WTI with chatbots, which we labelled the *apathetic customer*, depicts customers who experienced a disruptive situation as a peripheral condition. They experienced a configuration of values, including the social value of perceived anthropomorphism as a core condition, and the emotional value of perceived empathy and the functional values of perceived personalization, perceived benefit, and perceived objectivity as peripheral conditions. The epistemic value of curiosity is irrelevant for *apathetic customers'* WTI with chatbots.

The third sufficient configuration for WTI with chatbots, which we labelled the *pragmatic customer*, depicts customers who experienced a disruptive situation as a core condition. They experienced a configuration of values, including the epistemic value of curiosity as a core condition, and the emotional value of perceived empathy and the functional values of perceived benefit and perceived objectivity as peripheral conditions. *Pragmatic customers* do not experience the social value perceived anthropomorphism as a peripheral condition, and the functional value perceived personalization is irrelevant to their WTI with chatbots.

		WTI with chatbots				No WTI with chatbots
		Sensitive customer	Apathetic customer	Pragmatic customer	Fastidious customer	Rejecting customer
	Disruptive situation	●	•	●		
Emotional value	Perceived empathy	•	•	•	•	⊗
Epistemic value	Curiosity	●		●	•	⊗
Functional value	Perceived personalization	•	•		•	⊗
	Perceived benefit	•	•	•	•	⊗
	Perceived objectivity		•	•	•	⊗
Social value	Perceived anthropomorphism	●	●	⊗	●	⊗
	Raw coverage	0.44	0.43	0.26	0.60	0.35
	Unique coverage	0.03	0.02	0.10	0.19	0.35
	Consistency	0.98	0.98	0.92	0.93	0.99
	Solution coverage	0.74				0.35
	Solution consistency	0.92				0.99

FIGURE 2 Sufficient configurations for WTI and no WTI with chatbots.

The fourth sufficient configuration for WTI with chatbots, which we label the *fastidious customer*, depicts customers that experienced a configuration of all values, including the social value of perceived anthropomorphism as a core condition and the emotional value of perceived empathy, the epistemic value of curiosity, and the functional values of perceived personalization, perceived benefit, and perceived objectivity as peripheral conditions. Whether or not *fastidious customers* experienced a disruptive situation is irrelevant to their WTI with chatbots.

The sufficient configuration for no WTI with chatbots, which we labelled the *rejecting customer*, depicts customers who did not experience any emotional, epistemic, functional, or social values of chatbots as core conditions. Whether they experienced a disruptive situation or not is irrelevant to these customers.

We evaluated the sufficient configurations based on their consistency, raw coverage, and unique coverage. The consistency score describes the degree to which a sufficient configuration consistently leads to an outcome (Park, Fiss, & El Sawy, 2020). Raw coverage explains the proportion of observations of an outcome covered by a specific sufficient configuration (Schneider & Wagemann, 2010). Unique coverage describes the proportion of observations of an outcome exclusively covered by a specific configuration, that is, excluding the proportions covered by other sufficient configurations. The consistency scores of all five configurations exceed the minimum consistency of 0.75. All configurations are empirically relevant as the raw coverages of the sufficient configurations range from 0.26 to 0.60. The unique coverages of the configurations for WTI with chatbots range from 0.02 to 0.19, indicating moderate explanatory overlap (Park, Fiss, & El Sawy, 2020). The unique coverages of 0.10 for the *pragmatic customer* and 0.19 for the *fastidious customer* indicate that these two configurations have a high unique explanatory power, suggesting that they reflect complementary explanations for WTI with chatbots (Park, Fiss, & El Sawy, 2020). The unique coverages of 0.03 for the *sensitive customer* and 0.02 for the *apathetic customer* suggest that they have a higher explanatory overlap, indicating that they explain roughly the same set of cases and that one configuration can substitute for the other (Park, Fiss, & El Sawy, 2020).

5 | DISCUSSION

Disruptive situations, such as the COVID-19 outbreak, can serve as catalysts for customers' WTI with chatbots. We build on TCV to take a situational and configurational perspective to study how disruptive situations stimulate the relationship between values and WTI with chatbots. We develop propositions about the theoretical mechanisms *across* and *within* the sufficient configurations. We then discuss the implications and limitations of our study and suggest opportunities for future research.

5.1 | Theoretical mechanisms across the sufficient configurations

Emotional value is often considered to have a key role in explaining customer behaviour, whether it is interacting with digital content services (Mäntymäki et al., 2020) or the purchase of festival tickets (Lee et al., 2011). Our findings align with such findings, suggesting that perceived empathy is a prerequisite for customers to have a WTI with chatbots. Customers seek positive affective experiences when interacting with human advisors (Bailey et al., 2001). Similar to the support they receive from human advisors, customers need chatbots to empathise with their unique needs (Cheng et al., 2022), for example, when they seek interpersonal and individualised support for managing their finances (Eriksson & Söderberg, 2010). Thus, we suggest the following proposition (P):

P1. Customers must experience perceived empathy (i.e., emotional value) for a WTI with chatbots.

The literature also points to epistemic value as an important driver of customer behaviour in the context of novel technologies (Hedman et al., 2019). Chatbots pique customers' curiosity (Yi et al., 2015) and increase their interest in interacting with chatbots. For example, they encourage exploring how chatbots' functionalities support financial management. We argue that customers value that a chatbot enables them to solve a specific task faster or better (Jiang et al., 2023), offers fact-based advice that is perceived as less biased than advice from human advisors (Longoni & Cian, 2022), and provides personalised and understanding support (Lee et al., 2022). The chatbot serves as a substitute for interaction with a human advisor, so customers prefer chatbots that offer human-like assistance (Schanke et al., 2021). Our findings confirm that emotional, epistemic, functional, and social values benefit customer behaviour (Mäntymäki et al., 2020), such that the identified values drive WTI with chatbots symmetrically. In other words, customers who experience all these values have a WTI with chatbots (see *fastidious customer* in Figure 2), and those who experience none have no WTI with chatbots (see *rejecting customer* in Figure 2). Thus, we suggest the following proposition:

> **P2.** Customers have a WTI with chatbots when they experience all values (i.e., emotional, epistemic, functional, and social values) and no WTI with chatbots when they experience none of them, irrespective of whether they experience a disruptive situation.

While the same values apply in disruptive situations (Vázquez-Martínez et al., 2021), our findings show that disruptive situations allow customers to have a WTI with chatbots even if they do not perceive all the values. Customers who experience disruptive situations strive to minimise their negative consequences, which may lead them to change their behavioural patterns (Baumeister et al., 2001). For example, the COVID-19 outbreak disrupted many customers' financial management via human advisors, making them recognise chatbots as a means to minimise the bad consequences of the disruptive situation by interacting with them to sustain financial management. Disruptive situations have the power to lower customers' mental threshold for when perceived values are ample, making the relationship between values and WTI with chatbots more complex by enabling three additional, distinct pathways for WTI with chatbots (see *sensitive customer*, *apathetic customer*, and *pragmatic customer* in Figure 2). Thus, disruptive situations stimulate WTI with chatbots in an asymmetrical way, allowing some customers to interact with chatbots despite a lack of specific epistemic, functional, and social values, that is, curiosity, perceived objectivity, perceived personalization, or perceived anthropomorphism. We suggest the following proposition:

> **P3.** Disruptive situations stimulate WTI with chatbots, such that customers can have a WTI with chatbots even when they do not experience all values (i.e., epistemic, functional, and social values).

5.2 | Theoretical mechanisms within the sufficient configurations

For customers experiencing a disruptive situation, either curiosity (i.e., epistemic value) or perceived objectivity (i.e., functional value) are irrelevant as long as they experience all other values (see *sensitive customer* and *apathetic customer* in Figure 2). Customers prefer chatbots when seeking fact-based information because they perceive them as less biased than human advisors (Longoni & Cian, 2022), but this specific functional value is irrelevant for *sensitive customers'* WTI with chatbots in a disruptive situation as long as they value the chatbot in all other ways. They are curious about chatbots and use the disruptive situation as an impetus to explore how chatbots can support them, for example, in terms of financial management, irrespective of whether they believe that it provides fact-based advice. While these insights are consistent with suggestions found in IS research that curiosity contributes to technology use intentions (Chandra et al., 2012), the epistemic value curiosity is irrelevant for *apathetic customers'* WTI with chatbots as long as they perceive all other values, including perceived objectivity. Prioritising curiosity, perceived objectivity becomes irrelevant for *sensitive customers*, while it is the opposite for *apathetic customers*. Thus, we suggest the following proposition:

P4. Either curiosity (i.e., epistemic value) or perceived objectivity (i.e., functional value) is irrelevant to customers' WTI with chatbots as long as they experience all other values.

Our results indicate that customers can overcome a lack of perceived anthropomorphism (i.e., social value) as long as they experience perceived empathy (i.e., emotional value), curiosity (i.e., epistemic value), and perceived benefit and objectivity (i.e., functional values) (see *pragmatic customer* in Figure 2). Building on the illustration that customers prefer impartial advice (Longoni & Cian, 2022), this configuration suggests that some customers do not perceive chatbots as human-like social actors but appreciate that they offer objective assistance. The disruptive situation caused these customers to adjust (Maier et al., 2024) and urged the need for a novel way of interaction with organisations, such that those customers' curiosity toward novel technologies let them explore chatbots as an alternative way of interacting with organisations. By being curious about chatbots and experiencing them as empathetic, beneficial, and objective, *pragmatic customers* substitute for the lack of perceived anthropomorphism to have a WTI with chatbots. In line with configurational IS research theorising on substitution interdependencies (Pflügner et al., 2024), we suggest the following proposition:

P5. Customers can compensate for the lack of perceived anthropomorphism (i.e., social value) with perceived empathy (i.e., emotional value), curiosity (i.e., epistemic value), and perceived benefit and perceived objectivity (i.e., functional values) to have a WTI with chatbots, irrespective of perceived personalization.

5.3 | Theoretical implications

IS research on TCV considers values distinct and additive (Yang & Lin, 2017; Zhu et al., 2023). Thus, the more values customers perceive, the more likely they will interact with a technology. We confirm this symmetrical understanding of the relationship between values and behaviour, suggesting that customers who perceive all values have a WTI, and those who perceive none have no WTI (see *fastidious* and *rejecting customer* in Figure 2). Contrary to extant IS research on TCV, we show that the relationship between values and behaviour is more complex in disruptive situations. While customers experiencing all or no values still exhibit the same behaviour, the disruptive situation opens paths for customers who perceive only some of the values to have a WTI with chatbots. Either perceived objectivity or curiosity becomes irrelevant for customers' WTI with chatbots as long as they experience all remaining values (see *sensitive customer* and *apathetic customer* in Figure 2). In addition, customers can compensate for the lack of perceived anthropomorphism when they perceive other values, irrespective of perceived personalization (see *pragmatic customer* in Figure 2). Thus, the configurational perspective reveals that disruptive situations enable an asymmetric relationship between some values and WTI with chatbots, which would have been unidentifiable with a linear perspective (Levallet et al., 2021). Confirming the intuition that customers differ in how they weigh different values (Zeithaml et al., 2020), our findings highlight three additional, different paths toward customers' WTI with chatbots in disruptive situations. We, thus, provide a novel theoretical perspective on how values influence behaviour, suggesting that a configurational perspective is needed to capture the symmetrical and asymmetrical paths that explain behaviour.

We advance understanding of customer interactions with technologies such as chatbots, showing that disruptive situations from the broader environment unrelated to a specific technology, such as the COVID-19 outbreak, stimulate WTI with chatbots. For customers who experience a disruptive situation, it acts as a catalyst, such as in considering interacting with a chatbot to sustain interactions with organisations during an epidemic outbreak. Others who do not experience this situation as disruptive are not affected by it, highlighting that customers' perceptions of whether a situation is disruptive determine whether and how they are influenced by it. We move from extant explanations for technology interaction based on customers' perceptions of a technology's values (Mäntymäki et al., 2020) to one considering disruptive situations. We propose that there are disruption-stimulated configurations of values that explain technology interaction in combination with disruptive situations (see *sensitive*, *pragmatic*, and *apathetic customer* in Figure 2) and disruption-robust configurations that explain technology interaction irrespective of disruptive situations (see *fastidious* and *rejecting customer* in Figure 2). Connecting established value-based perspectives with a situational perspective (Burton-Jones et al., 2015), we explain technology interactions more comprehensively by considering the influence of disruptive situations. We follow the call to consider the situational context as a boundary condition for technology interaction (Venkatesh et al., 2016), illustrating how disruptive situations stimulate technology interactions, as seen with the COVID-19 outbreak and WTI with chatbots.

IS research has studied curiosity as a part of cognitive absorption (Agarwal & Karahanna, 2000). We consider curiosity as a distinct, relevant value that influences technology interaction in the context of chatbots. In doing so, we find that customers are driven by curiosity as an epistemic value to explore the possibilities that chatbots provide to support a specific task, such as handling financial matters. They seek to explore new or uncertain things (Kashdan et al., 2018), so closing this information gap is an important driver for their WTI with chatbots. While curiosity is not relevant for some customers (see *apathetic customer* in Figure 2), it is a driver for other customers' WTI with chatbots (see *sensitive customer* and *pragmatic customer* in Figure 2). Drawing on TCV's insights on epistemic values (Jang et al., 2018), we complement the picture of relevant values for technology interaction by identifying the epistemic value of curiosity as an important driver of WTI with chatbots.

We contribute to configurational IS research by providing insights into how a configurational perspective enables the identification of boundary conditions for complex outcomes such as customers' WTI with chatbots. Configurational IS research uses methods such as fsQCA in innovative ways to develop, test, and build theory (Iannacci et al., 2022; Meier et al., 2024; Park, Fiss, & El Sawy, 2020) or to theorise about configurational moderation (Ma et al., 2024). While configurational IS research traditionally offers rich insights into the theoretical mechanisms *within* sufficient configurations to explain how conditions interact to give rise to an outcome (Park, Pavlou, & Saraf, 2020), we show that leveraging theoretical mechanisms *across* sufficient configurations helps identify the boundary conditions under which configurations give rise to an outcome. By distinguishing the sufficient configurations that give rise to WTI with chatbots based on disruptive situations, we show that disruptive situations are a cause of asymmetry. We contribute to configurational IS research by demonstrating that theorising on theoretical mechanisms across sufficient configurations offers insights into important boundary conditions, such as disruptive situations that shape explanations of complex outcomes.

5.4 | Practical implications

Our results offer several practical insights for organisations that intend to foster their customers' interactions with chatbots, thereby reducing the cost of customer interactions.

Organisations should follow different strategies for promoting chatbots to address the multiple configurations influencing how customers engage with technologies. They should address the shared values across all strategies while at the same time focusing on the distinct values of each configuration. To maximise chatbot interactions in disruptive situations, organisations should profile customers along the identified configurations (see *sensitive*, *apathetic*, and *pragmatic customers* in Figure 2), for example, by surveying customers or analysing their prior interactions with human advisors. Based on the resulting categorization, they can ideally promote the chatbots to different customer types. To promote chatbots to *sensitive customers*, organisations should demonstrate that chatbots are an efficient and reliable alternative to human advisors that offer a similar level of personalised, empathetic assistance. To promote chatbots to *apathetic customers*, organisations should emphasise that chatbots combine empathetic, human-like assistance with impartial, rule-based advice. To promote chatbots to *pragmatic customers*, organisations should emphasise that customers can trust the chatbot with confidential requests they would not like to discuss with a human advisor because the chatbot offers fact-based, unbiased, and non-judgmental assistance.

Organisations must design empathetic chatbots that interact with customers in a way that signals understanding and responds to their individual needs. Chatbots should demonstrate interest in customers through conversational cues, such as explaining that customers have their individual attention and that they are committed to providing the best possible guidance to address customers' needs.

Organisations should ensure that chatbots are beneficial to customers. For example, in the banking context, they should provide easy and fast access to core functionalities such as managing one's finances (e.g., checking account balances). When customers say "balance", they could get a quick overview of a customer's bank accounts on one screen. Organisations should consider ways to speed up features within chatbots or offer specific standalone chatbots that provide quick access to a particular functionality.

TABLE 8 Boundary conditions and future research directions.

Boundary condition	Description
Chatbot type	• *Utilitarian versus hedonic chatbots*: Since we focus on chatbots for customer interaction, the investigated chatbots, such as banking chatbots that support financial management, are inherently utilitarian. While our findings point to different functional values as drivers of WTI with chatbots (i.e., perceived personalization, perceived benefit, perceived objectivity), these values may be less important for chatbots that serve primarily hedonic purposes. • *Availability of Alternatives*: We do not consider the availability of alternatives, such as self-service IS (Saeed & Abdinnour, 2013). Future research could contrast how the influence of disruptive situations on customers' WTI with chatbots differs depending on the availability of alternatives. • *Chatbot technology*: We do not distinguish between rule-based and generative AI chatbots. Future research should study how customers' interactions differ based on the chatbot technology.
Customer	• *Age*: Most interviewees and survey participants of this study are younger than 60, so our findings are particularly relevant for the WTI with chatbots of younger and middle-aged customers. Since research shows that customers from the age of 60 process information slower and interact with technology less performant (Tams, 2022), older customers might value chatbots less and may be more reluctant in terms of WTI with chatbots. Purposefully sampling older participants to explore age as a boundary condition allows for further contextualising of explanations for WTI with chatbots. • *Individual differences*: Some users might be predisposed to perceiving a specific situation as disruptive, so future research should investigate whether individual differences influence the perception of disruptive situations.
Disruptive situation	• *Different types*: We focus on disruptive situations as discontinuities from the broader environment (Morgeson et al., 2015). A promising direction for future research is to drill down into how different types of disruptive situations stimulate technology interaction to shed more light on the interplay between disruptive situations and values (Meier et al., 2022). • *Temporality*: We do not consider the temporality of disruptive situations. Since disruptive situations could diminish after a while, for example, because customers get used to a situation and perceive it as less disruptive, some customers might stop interacting with chatbots again. Future research could explore the temporality of disruptive situations, that is, whether the influence of disruptive situations diminishes after a while and whether the induced WTI with chatbots is persistent or temporary. • *Physiological factors*: We focus on established self-reported measures of disruptive situations. Future work should contrast these self-reported measures with customers' physiological arousal to measure disruptive situations (Ortiz de Guinea & Webster, 2013). • *Organisational context*: In addition to the literature on behaviour, a rich body of research offers insights into how innovations can disrupt organisations (Christensen et al., 2018). Connecting such work to the understanding of disruptive situations from the broader environment brought forward in this study offers avenues for exploring how disruptive situations from the broader environment shape organisations.

Disruptive situations in the broader environment can create opportunities to encourage customers to interact with chatbots that have not realised their potential. We illustrated how a situation that disrupts the way customers handle their financial matters creates an opportunity for banks to promote chatbots as a reliable and convenient way to manage finances. Chatbots can be designed and positioned as IS that help customers manage and respond to disruptive situations (Mendonça, 2007). When disruptive situations occur, we encourage managers to consider how they can educate customers on how to take full advantage of the technologies they offer.

5.5 | Limitations and future research

This research has limitations. We explain the situational context as one important boundary condition for WTI with chatbots in detail (i.e., disruptive situation vs. no disruptive situation) and expect our findings to be robust within the boundary conditions of the investigated chatbot type (i.e., chatbots used for customer interaction), interviewed and surveyed customers (i.e., young to middle-aged customers), and studied disruptive situations (i.e., disruptive situations stemming from the broader environment that affect customers' usual way of interacting with an organisation). A closer look at the different potential manifestations of these boundary conditions, also called scope conditions (Goertz & Mahoney, 2013), reveals future research directions worth exploring (see Table 8).

6 | CONCLUSION

Motivated by a desire to understand why the COVID-19 outbreak triggered growth in chatbot interactions, we investigated how disruptive situations stimulate the relationship between values and the WTI with chatbots. We draw from TCV to conduct a two-step empirical approach based on qualitative interviews and a scenario-based study in combination with fsQCA. The findings reveal three disruption-stimulated configurations and two disruption-robust configurations that explain WTI with chatbots. We extend the IS literature by uncovering how configurations of values influence WTI with chatbots, explaining that and how disruptive situations stimulate technology interaction, and illuminating the values that explain WTI with chatbots. We encourage future research that further contextualises our work against a backdrop of different disruptive situations.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in the Open Science Foundation at https://doi.org/10.17605/OSF.IO/FK3YQ.

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APPENDIX A: LITERATURE REVIEWS

We conducted a descriptive literature review (Paré et al., 2015) to get an overview of extant knowledge on chatbot interaction. We reviewed literature from eleven major IS research journals (Lowry et al., 2013) and additionally included Business & Information Systems Engineering, Internet Research, and Computers in Human Behaviour to capture emerging IS research topics. We used the Web of Science Database with the keyword "chatbot" for our literature search and included articles published between 1980 and 2023. We included articles focusing on chatbot interactions from an individual perspective and extracted the studied factors that influence chatbot interaction, the studied outcome, and the used theoretical lens (see Table A1).

We conducted a critical literature review (Paré et al., 2015) to determine how leveraging the key insights from TCV can advance IS research. We reviewed research using TCV from eleven major IS research journals (Lowry et al., 2013), again including Business & Information Systems Engineering, Internet Research, and Computers in Human Behaviour. We searched the Web of Science Database using the search string ("theory of consumption values" OR "customer value theory") and included articles published between 1980 and 2023. We critically assessed which values the articles included in their analyses, which outcome they studied, and which of TCV's key insights they used to understand technology interaction (see Table A2).

TABLE A1 Representative IS studies on chatbot interactions.

Reference	Major finding	Influencing factors	Outcome	Theoretical lens
(Araujo, 2018)	Human-like chatbots are associated with higher levels of anthropomorphism than machine-like chatbots. Anthropomorphic cues increase the emotional connection with the company.	Social: social presence, mindful anthropomorphism, mindless anthropomorphism	Emotional connection and satisfaction with the company	/
(Benke et al., 2022)	Higher control levels over chatbots increase autonomy and trust in chatbots while not increasing cognitive effort.	Functional: control level	Autonomy, trust, cognitive effort	/
(Chandra et al., 2022)	AI cognitive and emotional competencies increase user engagement with AI directly and through user trust in AI. AI relational competency does not influence user engagement with AI.	Functional: AI cognitive competency Emotional: AI emotional competency	User engagement with AI	Media naturalness theory
(Chen et al., 2021)	Customers perceive a higher cognitive fit if chatbots provide them with suggestive guidance and friendly communication. Perceived cognitive fit increases the perceived decision quality and perceived decision effort.	Functional: decisional guidance, perceived cognitive fit, perceived task complexity Social: communication style Other: shopping task	Perceived decision quality, perceived decision effort	Cognitive fit theory
(Cheng et al., 2022)	Perceptions of empathy and friendliness of chatbots influence trust. Task complexity negatively moderates the relationship between friendliness and trust. Disclosure of the text-based chatbot negatively moderates the relationship between empathy and trust. In contrast, it positively moderates the relationship between friendliness and trust. Trust increases the reliance on chatbots and decreases the resistance to chatbots in future interactions.	Emotional: perceived empathy, friendliness, trust Other: task complexity, disclosure of the chatbot	Reliance, resistance	Stimulus-organism-response model
(Gnewuch et al., 2022)	A delayed response time increases social presence for novice users but decreases it for experienced users. Social presence increases use intention.	Functional: response time Social: social presence Other: chatbot experience	Use intention	Social response theory, expectation violation theory
(Go & Sundar, 2019)	High message interactivity increases social presence, perceived homophily, perceived contingency, and perceived dialogue. Social presence, perceived homophily, and perceived dialogue increase attitude and behavioural intention to return to a chatbot.	Functional: message interactivity, perceived contingency Social: perceived anthropomorphism, social presence, perceived homophily, perceived dialogue, human identity cues	Attitude, behavioural intention to return to a chatbot	/

(Continues)

TABLE A1 (Continued)

Reference	Major finding	Influencing factors	Outcome	Theoretical lens
(Grimes et al., 2021)	Conversational capability increases customers' conversational engagement. The relationship is moderated by expectation violation, such that it is more positive for customers whose expectations were exceeded.	Functional: conversational AI capability Other: expectation setting, expectation violation	Conversational engagement	Expectation violation theory
(Han et al., 2022)	AI-expressed positive emotion increases customer's positive emotion and expectation-disconfirmation. Customer's positive emotion increases service quality and satisfaction, and expectation-disconfirmation decreases service quality and satisfaction. Customers' relationship norm orientation (i.e., communal-oriented customers vs. exchange-oriented customers) moderates the relationship between AI-expressed positive emotion and expectation-disconfirmation.	Emotional: AI-expressed positive emotion, customers' positive emotion Other: expectation-disconfirmation, relationship norm orientation	Service quality, satisfaction	/
(Hill et al., 2015)	Humans communicate with chatbots for longer durations but with shorter messages compared to humans. Conversations with chatbots lack the richness of vocabulary from human-to-human conversations and exhibit greater profanity.	/	Communication style (vocabulary richness, profanity)	/
(Huang & Lee, 2022)	Social interactivity cues, social credence cues, and social sharing signs and language cues increase emotional arousal. Emotional arousal increases attitude toward the fintech chatbot, increasing continuance intention.	Emotional: emotional arousal Social: social interactivity cues, social credence cues, social sharing signs and language cues Other: attitude toward the chatbot	Continuance intention	Social response theory
(Jiang et al., 2022)	Responsiveness and conversational tone increase chatbot satisfaction. Chatbot satisfaction increases customers' social media engagement, which in turn increases price premium and purchase intention.	Functional: responsiveness Social: conversational tone Other: satisfaction, social media engagement	Price premium, purchase intention	Social exchange theory, resource exchange theory
(Jiang et al., 2023)	Human-like cues and tailored responses increase social presence and perceived task-solving competence. Social presence and perceived task-solving competence increase trust.	Functional: perceived task-solving competence Social: human-like cues, social presence, tailored response	Trust	Task-technology fit theory

TABLE A1 (Continued)

Reference	Major finding	Influencing factors	Outcome	Theoretical lens
(Konya-Baumbach et al., 2023)	Anthropomorphism increases trust, purchase intention, word of mouth, and satisfaction with the shopping experience through social presence.	Social: anthropomorphism, social presence	Trust, purchase intention, word of mouth, satisfaction with the shopping experience	Social presence theory
(Lee et al., 2022)	Emotional support, informational support, and esteem support increase social attraction and emotional credibility. Social attraction and credibility increase affective attachment and purchase intention.	Emotional: emotional support, emotional credibility, esteem support Functional: information support Social: social attraction	Affective attachment, purchase intention	Social support theory
(Liu et al., 2023)	Relevance, completeness, pleasure, and assurance increase satisfaction with task-oriented chatbots. Satisfaction increases chatbot use intention. Response time and empathy increase satisfaction in Mainland China but not in Hong Kong.	Emotional: pleasure, assurance, empathy Functional: relevance, completeness, response time	Satisfaction, use intention	Information success model
(Lu et al., 2022)	Perceived humanness (i.e., conversational human voice, anthropomorphism, social presence) increases perceived relational investment and trust in the organisation.	Social: perceived humanness	Perceived relational investment, trust in the organisation	/
(Mou & Xu, 2017)	Users demonstrate different personality traits and communication attributes when interacting with humans compared to chatbots.	/	Self-disclosure	Computers are social actors, Cognitive-affective processing system
(Nguyen et al., 2022)	The perceived autonomy of chatbots increases customers' perceptions of their competence and satisfaction with their performance. Cognitive effort decreases perceived competence and system satisfaction. Perceived competence increases performance satisfaction and system satisfaction.	Functional: cognitive effort, perceived competence Other: perceived autonomy	Performance satisfaction, system satisfaction	Self-determination theory
(Park et al., 2021)	Users' ethical orientation of idealism and the perceived humanlikeness of chatbots influence the use of profanity and offensive language when interacting with a chatbot.	Social: perceived human-likeness Other: ethical ideology	Communication style (profanity and offensive language)	/

(Continues)

TABLE A1 (Continued)

Reference	Major finding	Influencing factors	Outcome	Theoretical lens
(Pentina et al., 2023)	Anthropomorphism and authenticity increase chatbot social interaction. Chatbot social interaction increases attachment moderated by motivation (e.g., using a chatbot to satisfy social needs vs. using it for fun).	Functional: authenticity Social: anthropomorphism Other: motivation	Chatbot social interaction, attachment	/
(Rhee & Choi, 2020)	Personalization and social role (assistant vs. friend) influence building attitudes toward a product. The attitude toward a product is higher for chatbots with the role of a friend.	Functional: personalization Social: social role (assistant vs. friend)	Attitude toward a product	Elaboration likelihood model, heuristic-systematic model, social role theory
(Schanke et al., 2021)	Perceived anthropomorphism (i.e., humour, communication delays, social presence) increases transaction conversion.	Social: perceived anthropomorphism	Transaction conversion (selling of used clothes)	/
(Schuetzler et al., 2019)	Enhanced conversational skill increases response latency. Tailored responses increase strategic behaviour to manage response latency when customers deceive.	Social: conversational skill	Response latency, hesitations	Interpersonal Deception Theory
(Schuetzler et al., 2020)	The conversational skills of a chatbot in terms of tailored responses and response variety, together with social presence, influence perceived humanness and partner engagement.	Social: conversational skill	Mindful anthropomorphism (perceived humanness), mindless anthropomorphism (partner engagement)	Social presence theory
(Shin et al., 2022)	The cultural and social context of chatbot interactions influences how users interact with chatbots and how they perceive chatbot news. Perceived fairness, perceived accountability, perceived transparency, and media trust influence algorithmic trust. Algorithmic trust influences emotional valence through accuracy and personalization.	Emotional: perceived fairness, algorithmic trust Functional: perceived accountability, perceived transparency, accuracy, personalization Other: media trust	Emotional valence	/

TABLE A1 (Continued)

Reference	Major finding	Influencing factors	Outcome	Theoretical lens
(Shumanov & Johnson, 2021)	User personality can be predicted with contextual interactions, and chatbots can be manipulated to assume a personality. Matching user personality with chatbot personality positively impacts user engagement with chatbots and purchasing outcomes.	Other: chatbot personality	Chatbot engagement, purchasing behaviour	Similarity attraction theory, five-factor model of personality
(van den Broeck et al., 2019)	Perceived intrusiveness of chatbots decreases message acceptance. Message acceptance increases patronage intentions.	Other: perceived intrusiveness, message acceptance	Patronage intention (likelihood of buying the product offered by the chatbot)	/

TABLE A2 Representative IS studies using TCV.

Context	Values	Outcome	1. Key insight[a]	2. Key insight[a]	3. Key insight[a]	Reference
Digital content services	Emotional value (enjoyment), functional value (ubiquity), social value (social connectivity), epistemic value (discovery of new content)	Upgrade to premium intention, retain premium intention	Fully used.	Not used.	Not used.	(Mäntymäki et al., 2020)
Gaming	Enjoyment value, character competency value, visual authority value, monetary value	Game item purchase intention	Fully used.	Not used.	Not used.	(B.-W. Park & Lee, 2011)
	Learning, novelty, escapism, enjoyment, social value, audio-visual value, value for money	Gamer loyalty	Fully used.	Not used.	Not used.	(Teng, 2018)
Health and fitness apps	Functional value (physical appearance, general health), emotional value (enjoyment), epistemic value (learning), social value (social interaction, affiliation), conditional value (condition)	Use intention	Fully used.	Not used.	Not used.	(Zhu et al., 2023)
Hedonic digital artefacts	Visual/musical appeal value, social value, playfulness value, value for money	Use intention, positive word-of-mouth intention	Fully used.	Not used.	Not used.	(Turel et al., 2010)
Social networking sites (SNS)	Functional value (price utility, functional quality), emotional value (aesthetics, playfulness), social value (social self-image expression, social relationship support)	Digital items purchase intention	Fully used.	Not used.	Not used.	(H.-W. Kim et al., 2011)
	Functional value (network management), social value (social image), epistemic value (learning), emotional value (enjoyment), conditional value (risk)	Continuous use intention	Fully used	Not used	Not used	(Chen & Sharma, 2013)
	Functional value (perceived convenience, perceived benefit), social value (social relationship creation, social relationship maintenance), emotional value (perceived relaxation, perceived playfulness), epistemic value (perceived novelty)	Continuous use intention	Fully used.	Not used.	Not used.	(Yang & Lin, 2017)

TABLE A2 (Continued)

Context	Values	Outcome	1. Key insight[a]	2. Key insight[a]	3. Key insight[a]	Reference
	Functional value (convenience of SNS gifting), monetary value (gift price fairness), social value (relationship support of SNS gifting), emotional value (pleasure of SNS gifting)	SNS gifting intention	Fully used.	Not used.	Not used.	(S.-H. Lee et al., 2020)
Social virtual world (SVW)	Value for money (e.g., benefits from a premium user account), epistemic value (e.g., inadequate experience of the basic user account), functional value (e.g., decoration with virtual items to customise virtual space), social value (e.g., status enhancement through a premium account), and emotional value (e.g., engagement with the service)	Virtual purchasing	Fully used.	Not used.	Not used.	(Mäntymäki & Salo, 2015)

[a]The first key insight suggests that different values influence behaviour. The second key insight suggests that customers' perceptions of situations stimulate how values form behaviour. The third key insight suggests that values collectively contribute to behaviour, and customers follow different reasoning for their behaviour.

APPENDIX B: QUALITATIVE STUDY

B.1. | Q-sorting approach

To validate the assignment of the values of *perceived empathy*, *curiosity*, *perceived personalization*, *perceived benefit*, *perceived objectivity*, and *perceived anthropomorphism* to the TCV categories of *emotional*, *epistemic*, *functional*, and *social value*, we conducted a Q-sorting approach, which is commonly used in IS research (MacKenzie & Podsakoff., 2011). We recruited 18 participants who were familiar with chatbots. One of the participants had a bachelor's degree, 16 had a master's degree, and one had a PhD degree. The participants were presented with the definition of the four value types (see Table 1) and a definition with two sample items for each identified value (see Table 4). Based on the definitions and sample items, they assigned each value to one value type. We then used their assignment to calculate the hit rate (Landis & Koch, 1977; Nahm et al., 2002), which indicates the extent to which a value was categorised into the correct value type. We calculated the hit rate for each identified value by dividing the number of correct placements to a value type by the total placements. The hit rates of the values range from 0.61 to 0.83 (see Table B2), indicating that each value was correctly assigned to a value type with more than 60 percent.

TABLE B1 Interview guideline.

Section	Description
Opening	• Introduction of the interviewer
Introduction	• Explanation of the interview procedure • Banking chatbots Are you familiar with chatbots in general? Are you familiar with banking chatbots? Does your bank offer a banking chatbot? Have you ever interacted with a banking chatbot? Which functionalities of the banking chatbot do you use?
Key questions	• What are the reasons that make you consider interacting with a banking chatbot? • Please describe the reasons in as much detail as possible. (“Laddering”) • Did the COVID-19 outbreak influence how you handle financial matters?
Closing	• Collecting personal information about the interviewees (age, biological sex, profession) • Ask for further potential interviewees (“Snowballing”)

TABLE B2 Q-sorting approach.

	Emotional value	Epistemic value	Functional value	Social Value	No or other assignment
Perceived empathy	**0.83**	-	-	-	0.17
Curiosity	-	**0.83**	-	-	0.17
Perceived personalization	-	-	**0.67**	-	0.33
Perceived benefit	-	-	**0.83**	-	0.17
Perceived objectivity	-	-	**0.83**	-	0.17
Perceived anthropomorphism	-	-	-	**0.61**	0.39

Note: Numbers in bold indicate that the hit rate is above 61%, which means the categorization is valid.

TABLE B3 Validation of qualitative findings.

Category of validity	Validation
Design validity	We ensured descriptive validity with a detailed description of the research process. We ensured credibility and transparency with a sufficiently large sample (Sarker et al., 2013). We ensured transferability by drawing on an established theory.
Analytical validity	We ensured plausibility and theoretical validity by grounding the interview structure on the TCV (Sheth et al., 1991). We left room for unforeseen questions while at the same time preserving consistency within the structure by following a semi-structured approach.
Inferential validity	We mirrored answers to the participants to ensure a correct understanding of descriptions and greater interpretative validity. We grounded the coding based on answers by applying descriptive and interpretive coding (Myers, 2019).

Note: Design validity describes the extent to which a qualitative study was well designed and performed, ensuring that the findings are credible and transferable. Analytical validity describes the extent to which qualitative data were well collected and analysed, ensuring that the findings are dependable, consistent, and plausible. Inferential validity describes the quality of interpretation, reflecting the extent to which others can confirm or corroborate the findings (Venkatesh et al., 2013).

Since all values have a hit rate of at least 61 percent (Tarafdar et al., 2020), we concluded that the assignment of values to the categorizations is valid.

APPENDIX C: QUANTITATIVE STUDY

Scenario A: The COVID-19 outbreak as a disruptive situation for handling financial matters. You go to the bank every week to manage your finances. You always consult your personal advisor at the bank, who assists you with various tasks, such as checking your account balance and making money transfers. When the COVID-19 pandemic broke out, you limited direct contact with other people as much as possible to protect yourself and others from catching the virus. Since you do not want to go to the bank to consult your personal advisor, the pandemic outbreak makes it essential for you to find a way to manage your finances. It severely affects how you usually handle financial matters because you can no longer rely on assistance from your personal bank advisor. As a result, you do not know how to respond to this situation regarding handling financial matters.

Scenario B: The COVID-19 outbreak as no disruptive situation for handling financial matters. You handle your financial matters by yourself without assistance from a personal bank advisor. To accomplish various tasks such as checking your account balance or making money transfers, you prefer using your bank's online services. When the COVID-19 pandemic broke out, you limited direct contact with other people as much as possible to protect yourself and others from catching the virus. Since you can still use online services without going to the bank, the pandemic outbreak is not essential for you in managing your finances. It does not affect how you usually handle financial matters because you manage your finances without a personal bank advisor. As a result, you know how to respond to this situation regarding handling financial matters.

C.1. | fsQCA

Calibration. In line with previous IS research (Mattke et al., 2021), we computed the mean of each construct and used the direct calibration function to calculate the mean values to fuzzy set memberships (Ragin & Davey, 2016). We used calibration anchors based on the seven-point Likert scale used rather than the data distribution to avoid

TABLE C1 Screening questions.

Screening question	Required answer
Are you familiar with banking chatbots?	Yes
Examples of banking chatbots are Alexa from Amazon and Siri from Apple.	No
Does your bank offer a banking chatbot?	Yes
Which of the following functionalities are typically *not* provided by banking chatbots?	Provide information about a bank account or credit card: No Assist with financial transactions: No Order food for delivery: Yes Answer frequently asked questions about a bank account or credit card: No Send messages to friends and family: Yes

obscuring the meaningful data gathered by the Likert scale and bounding the calibration to a specific data set (Mattke et al., 2022; Wagemann et al., 2016). Following best practice in configurational IS research (Park et al., 2017), we used two of the seven-point Likert scale as calibration anchor for full-non-membership ("disagree"), the mean value of four as the cross-over point ("neither disagree nor agree"), and the value six for full membership ("agree"). We applied this calibration to the identified values, disruptive situation, and the WTI with chatbots. To ensure that no observations were excluded from the fsQCA, we avoided fuzzy set memberships of 0.50 by subtracting a small constant of 0.00001 (Fiss, 2011).

Analysis for necessary conditions. We performed the analysis for necessary conditions using fsQCA for WTI with chatbots and no WTI with chatbots. To be defined as necessary, a condition must exceed a consistency threshold of 0.90, a coverage threshold of 0.60, and a relevance of necessity threshold of 0.60 (Thomann et al., 2018). Consistency describes the degree to which customers with the same condition share the same outcome (Ragin, 2008). The coverage describes the degree of data covered by a condition, and the relevance of necessity explains how relevant a condition is as a necessary condition. While a low relevance of necessity indicates that a condition is rather trivial, a high relevance of necessity shows that a condition is highly relevant. By considering coverage and relevance of necessity, we avoid trivial necessary conditions (type 1 error) (Ragin, 2006).

Analysis for sufficient configurations. We analysed WTI with chatbots and no WTI with chatbots for sufficient configurations. We first created a truth table based on the seven conditions and the outcome. The truth table consists of 2^k logical possible configurations, with k representing the number of investigated conditions. Since we analysed seven conditions, the truth table consisted of 128 possible configurations. We applied a frequency threshold of three to reduce the truth table (Maggetti & Levi-Faur, 2013), which is consistent with previous IS research (Maier et al., 2021). The reduced truth table includes about 80 percent of the initial observations (123 of 153 observations, see Table C4 in Appendix C), showing that it still includes a significant part of the observations after applying the threshold (Mattke et al., 2022). We applied a raw consistency threshold of 0.85 (Iannacci & Cornford, 2018), which exceeds the minimum raw consistency threshold and improves the reliability of the results (Ragin, 2008). The raw consistency threshold sets a minimum degree of how consistent configurations result in an investigated outcome. To avoid solutions that represent a present and absent outcome simultaneously, we applied a proportional reduction of inconsistency (PRI) threshold of 0.75 (J.-N. Lee et al., 2019), which is close to the chosen raw consistency threshold and higher than 0.50 (Greckhamer et al., 2018; Mattke et al., 2022) (see Tables C4 and C5 in Appendix C). We simplified the remaining truth table using the Quine McCluskey algorithm to create sufficient configurations. This algorithm can create 'don't care situations', which means that a condition in a specific configuration can be either present or absent, hence is not influencing the outcome in this configuration. The resulting solution is based solely on empirical data and reflects the complex solution (Pappas & Woodside, 2021).

TABLE C2 Measurement items.

Construct	Measure	Loading
Disruptive situation (adapted from Morgeson, 2005)	The COVID-19 outbreak disrupted my ability to get financial matters done.	0.96
	The outbreak of COVID-19 caused me to stop and think about how to handle financial matters.	0.77
	The outbreak of COVID-19 altered my normal way of handling financial matters.	0.97
Perceived empathy (adapted from Cheng et al., 2022)	{CHATBOT} would usually understand my specific needs.	0.84
	{CHATBOT} would usually give me individual attention.	0.85
	{CHATBOT} would be available whenever it is convenient for me.	n.s.*
	If I would require help, {CHATBOT} would do its best to help me.	0.81
Curiosity (adapted from Agarwal & Karahanna, 2000)	Using {CHATBOT} would excite my curiosity.	0.93
	Interacting with {CHATBOT} would make me curious.	0.90
	Using {CHATBOT} would arouse my imagination.	0.89
Perceived personalization (adapted from Shao et al., 2021)	{CHATBOT} could understand my needs when responding to my requests.	0.85
	{CHATBOT} would be personalised.	0.88
	{CHATBOT} would provide me customised services.	0.89
Perceived benefit (adapted from D. J. Kim et al., 2009)	Using {CHATBOT} would be convenient.	0.79
	I could save money by using {CHATBOT}.	0.77
	I could save time by using {CHATBOT}.	0.84
	Using {CHATBOT} would enable me to accomplish a financial task more quickly than using my traditional way of handling financial matters.	0.86
	Using {CHATBOT} would increase my productivity in handling financial matters (e.g., making transactions or finding financial information within the shortest time frame).	0.86
Perceived objectivity (adapted from Uhlmann & Cohen, 2007)	{CHATBOT}'s view of the world would be realistic.	0.76
	{CHATBOT} would be objective when making judgements and decisions.	0.79
	{CHATBOT} would be even-handed when weighing evidence that is relevant to a decision.	0.81
	{CHATBOT} would try to do what seems reasonable and logical.	0.78
	{CHATBOT} would try to objectively consider all of the facts it has access to when forming an opinion.	0.74
	{CHATBOT}'s judgements would be based on a logical analysis of the facts.	0.72
	{CHATBOT}'s decision-making would be rational and objective.	0.76
Perceived anthropomorphism (adapted from Li & Sung, 2021)	{CHATBOT} would have intentions.	0.86
	{CHATBOT} would have free will.	0.95
	{CHATBOT} would experience emotions.	0.94
	{CHATBOT} would have consciousness.	0.92
	{CHATBOT} would have a mind of its own.	0.93
Willingness to interact (adapted from Samochowiec & Florack, 2010)	I would be willing to spend my time with {CHATBOT}.	0.90
	I could imagine learning more about {CHATBOT}.	0.87
	If {CHATBOT} would seek contact with me, I would respond to that.	0.89
	I would be interested in a dialogue with {CHATBOT}.	0.91

Note: Marked items (n.s.*) were dropped due to bad loadings, indicating non-significance. We measured all items with a seven-point Likert scale (1 = "Strongly disagree" to 7 = "Strongly agree").

TABLE C3 Cross loadings.

	Perceived empathy	Curiosity	Perceived personalization	Perceived benefit	Perceived objectivity	Anthropomorphism	Willingness to interact	Disruptive situation	CMB marker
empatSQ01	**0.84**	0.63	0.71	0.61	0.50	0.53	0.55	0.19	0.18
empatSQ02	**0.85**	0.54	0.52	0.41	0.42	0.45	0.57	0.11	0.07
empatSQ04	**0.81**	0.47	0.47	0.56	0.55	0.22	0.49	0.09	0.15
curioSQ01	0.63	**0.93**	0.52	0.57	0.42	0.50	0.62	0.12	0.08
curioSQ02	0.56	**0.90**	0.48	0.57	0.42	0.45	0.55	0.20	0.01
curioSQ03	0.61	**0.89**	0.53	0.46	0.39	0.62	0.57	0.15	0.06
personSQ01	0.63	0.51	**0.85**	0.63	0.39	0.44	0.46	0.13	0.18
personSQ02	0.61	0.44	**0.88**	0.50	0.36	0.45	0.36	0.12	0.13
personSQ03	0.56	0.51	**0.89**	0.53	0.38	0.48	0.45	0.13	0.10
perbenSQ01	0.50	0.34	0.49	**0.79**	0.49	0.04	0.41	0.09	0.18
perbenSQ02	0.57	0.54	0.61	**0.77**	0.35	0.43	0.46	0.13	0.03
perbenSQ03	0.52	0.45	0.52	**0.84**	0.44	0.15	0.41	0.05	0.30
perbenSQ04	0.51	0.55	0.49	**0.86**	0.42	0.25	0.52	0.12	0.10
perbenSQ05	0.47	0.52	0.53	**0.86**	0.41	0.31	0.45	0.14	0.05
perobjSQ01	0.56	0.54	0.49	0.52	**0.76**	0.58	0.53	0.03	0.16
perobjSQ02	0.45	0.38	0.39	0.36	**0.79**	0.32	0.41	0.07	0.20
perobjSQ03	0.47	0.38	0.38	0.39	**0.81**	0.33	0.45	0.07	0.14
perobjSQ04	0.45	0.24	0.26	0.37	**0.78**	0.16	0.34	0.08	0.19
perobjSQ05	0.43	0.36	0.31	0.43	**0.74**	0.17	0.36	0.13	0.11
perobjSQ06	0.35	0.18	0.11	0.29	**0.72**	0.01	0.33	0.06	0.15
perobjSQ07	0.36	0.22	0.24	0.29	**0.76**	0.11	0.32	0.01	0.17
antropSQ01	0.52	0.53	0.44	0.29	0.39	**0.86**	0.54	0.18	0.00
antropSQ02	0.48	0.55	0.52	0.30	0.34	**0.95**	0.55	0.16	0.04
antropSQ03	0.42	0.51	0.51	0.26	0.30	**0.94**	0.49	0.16	0.07
antropSQ04	0.39	0.53	0.47	0.26	0.29	**0.92**	0.48	0.19	0.05
antropSQ05	0.41	0.52	0.45	0.24	0.26	**0.93**	0.52	0.11	0.01

TABLE C3 (Continued)

	Perceived empathy	Curiosity	Perceived personalization	Perceived benefit	Perceived objectivity	Anthropomor-phism	Willingness to interact	Disruptive situation	CMB marker
w2iSQ01	0.59	0.61	0.46	0.54	0.52	0.49	**0.90**	0.18	0.14
w2iSQ02	0.57	0.49	0.36	0.47	0.49	0.42	**0.87**	0.14	0.16
w2iSQ03	0.57	0.59	0.45	0.46	0.429	0.56	**0.89**	0.26	0.13
w2iSQ04	0.59	0.59	0.48	0.50	0.45	0.56	**0.91**	0.19	0.08
disruptSQ01	0.14	0.17	0.16	0.12	0.04	0.17	0.18	**0.96**	0.11
disruptSQ02	0.06	0.02	0.04	0.03	0.08	0.02	0.05	**0.77**	0.05
disruptSQ03	0.18	0.19	0.15	0.15	0.02	0.19	0.25	**0.97**	0.06
cmbmarker	0.16	0.05	0.16	0.16	0.21	0.04	0.14	0.08	**1.00**

Note: Cross loadings for items that correspond to the respective construct are displayed bold.

TABLE C4 Truth table for WTI with chatbots.

	PE	CU	PP	PB	PO	PA	DS	WTI	Number	Raw consistency	PRI
	1	0	1	1	1	1	1	1	3	0.98	0.93
	1	1	1	1	1	1	1	1	36	0.98	0.97
	1	1	1	1	0	1	1	1	4	0.97	0.91
	1	1	0	1	1	0	1	1	4	0.96	0.82
	1	1	1	1	1	0	1	1	9	0.92	0.79
	1	1	1	1	1	1	0	1	27	0.90	0.83
	1	0	1	1	1	0	1	0	4	0.93	0.68
	1	0	0	1	1	0	0	0	4	0.86	0.40
	1	0	1	1	1	0	0	0	5	0.86	0.48
	0	0	1	1	1	0	0	0	3	0.85	0.29
	1	1	1	1	1	0	0	0	13	0.84	0.56
	0	0	0	0	0	0	1	0	5	0.76	0.04
Relative Banzhaf index	0.20	0.13	0.13	0.20	0.13	0.06	0.13	-	-	-	-

Abbreviations: CU, curiosity; DS, disruptive situation; PA, perceived anthropomorphism; PB, perceived benefit; PE, perceived empathy; PO, perceived objectivity; PP, perceived personalization; WTI, willingness to interact.

fsQCA uses counterfactual analysis to make use of rows without empirical observations. Drawing on theoretical logic or substantive knowledge, 'easy' counterfactuals can be used to identify the intermediate solution (Park, Fiss, & El Sawy, 2020). While we identified the relevant values for WTI with chatbots with the qualitative study (see Table 4), TCV suggests that customers differ in how they evaluate and weigh the relevance of the values for their behaviour (Sweeney & Soutar, 2001). Hence, neither the qualitative study nor TCV offers specific insights into how the identified values work in configurations to result in WTI or no WTI with chatbots. To reflect this in the fsQCA, we refrain from drawing on theoretical logic or substantive knowledge in the counterfactual analysis (Park, Fiss, & El Sawy, 2020) so that the intermediate solution matches the complex solution.

By using 'easy' and 'difficult' counterfactuals, fsQCA identifies the parsimonious solution (see Figure C1) (Park, Pavlou, & Saraf, 2020). Combining the intermediate and parsimonious solution allows us to identify core and peripheral conditions (Pappas & Woodside, 2021). Since the intermediate solution matches the complex solution in our study, we essentially combine the complex solution with the parsimonious solution. The core conditions reflect the conditions included in the parsimonious solution that have a strong causal relationship with the outcome. The peripheral conditions reflect the conditions only included in the complex solution with a weaker causal relationship with the outcome (Fiss, 2011).

C.2. | Validation

C.3. | Common method bias

We applied Harman's single-factor test to check for common method bias (CMB) (Podsakoff & Organ, 1986). It showed that 39.02 percent of the variance of the data is explained with only one factor, which is below the

TABLE C5 Truth table for no WTI with chatbots.

	PE	CU	PP	PB	PO	PA	DS	WTI	Number	Raw consistency	PRI
	0	0	0	0	0	0	1	1	5	0.99	0.96
	0	0	0	0	0	0	0	1	6	0.99	0.96
	0	0	1	1	1	0	0	0	3	0.94	0.71
	1	0	0	1	1	0	0	0	4	0.91	0.60
	1	0	1	1	1	0	0	0	5	0.86	0.49
	1	0	1	1	1	0	1	0	4	0.84	0.31
	1	1	0	1	1	0	1	0	4	0.80	0.18
	1	1	1	1	1	0	0	0	13	0.78	0.40
	1	0	1	1	1	1	1	0	3	0.75	0.07
	1	1	1	1	0	1	1	0	4	0.71	0.09
	1	1	1	1	1	0	1	0	9	0.70	0.20
	1	1	1	1	1	1	0	0	27	0.48	0.16
Relative Banzhaf index	0.23	0.23	0.08	0.08	0.08	0.23	0.08				

Note: CU, curiosity; DS, disruptive situation; PA, perceived anthropomorphism; PB, perceived benefit; PE, perceived empathy; PO, perceived objectivity; PP, perceived personalization; WTI, no willingness to interact.

		WTI with chatbots		No WTI with chatbots					
	Disruptive situation		●						
Emotional value	Perceived empathy				⊗	⊗			
Epistemic value	Curiosity		●				⊗		
Functional value	Perceived personalization				⊗			⊗	
	Perceived benefit			⊗					
	Perceived objectivity					⊗	⊗	⊗	⊗
Social value	Perceived anthropomorphism	●							⊗
	Raw coverage	0.70	0.57	0.54	0.49	0.49	0.54	0.48	0.57
	Unique coverage	0.24	0.12	0.05	0.03	0.00	0.00	0.00	0.02
	Consistency	0.90	0.92	0.88	0.90	0.94	0.92	0.91	0.89
	Solution coverage	0.81		0.71					
	Solution consistency	0.87		0.82					

FIGURE C1 Parsimonious solution for WTI and no WTI with chatbots.

TABLE C6 Validation of quantitative findings.

Category of validity	Validation
Design validity	The Constructs are adapted from previous research (see Table C2 in Appendix C). Sample sizes are sufficient. The study is based on TCV (Sheth et al., 1991) to ensure internal validity. The highly generalizable design ensures external validity. Common method bias is not an issue (see Appendix C).
Measurement validity	Content validity, indicator reliability, construct reliability, and discriminant validity are no issues. The solutions are robust to adaptations in calibration anchors and frequency thresholds (Park, Fiss, & El Sawy, 2020) (see Appendix C).
Inferential validity	The solutions are reliable and robust due to high consistency and frequency thresholds (Schneider & Wagemann, 2012).

Note: Design validity describes the extent to which a quantitative study has internal and external validity. Measurement validity describes the extent to which an instrument accurately measures the intended construct according to its definition. Inferential validity describes the extent of the appropriate use of a method to infer the results (Venkatesh et al., 2013).

threshold of 50 percent. We also examined the correlation matrix (see Table 7), showing that all correlations are below the threshold of 0.90 (Pavlou et al., 2007). We followed the recommendation to include a theoretically unrelated marker variable ("I like to read") in the bivariate correlation matrix (Lindell & Whitney, 2001). The highest correlation was 0.21, showing that CMB is not an issue.

C.4. | Robustness tests

We tested the solutions for WTI and no WTI with chatbots for sensitivity to the sample (Maggetti & Levi-Faur, 2013; Schneider & Wagemann, 2010). We increased the frequency threshold to four, so configurations with less than four observations are dropped. After applying this frequency threshold, the revised truth table includes about 73 percent of the initial observations (112 of 153 observations), and the repeated analysis showed similar results. To test for sensitivity to calibration, we changed the calibration anchors to the minimum value of one, the mean value of four, and the maximum value of seven. The repeated analysis showed the same results. We also changed the raw consistency threshold to 0.80 (Greckhamer et al., 2018), and the analysis, again, showed the same results, which underlines the robustness of our results.