



Article

Exploring the Customer Experience Regarding AI-Powered Fintech Chatbots in Terms of SOR Theory

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Abstract

This study examines how the design and interaction features of AI-powered fintech chatbots shape the customer experience of Generation Z users by integrating the Stimulus-Organism-Response framework with dual-process perspectives. Two cross-sectional surveys were conducted in Türkiye. Study 1 (n = 166) examines the effect of social presence, interactivity, visual appeal, design originality, and usability on perceived competence and perceived warmth, which, in turn, shape the customer experience. Social presence and design originality significantly increased perceived competence ($\beta = 0.47, p < 0.001$), while visual appeal enhanced perceived warmth ($\beta = 0.32, p < 0.001$). Together, competence and warmth explained a substantial proportion of customer experience ($R^2 \approx 0.60$). Usability and interactivity showed no significant effects. Study 2 (n = 195) replicated these findings with trained users and introduced task complexity as a moderator. Under high task complexity, usability and interactivity became significant predictors of competence, which emerged as the primary driver of customer experience, whereas the influence of warmth diminished. Non-normal data distributions justified the use of Partial Least Squares Structural Equation Modeling. Overall, the findings suggest a shift from heuristic to systematic processing as fintech tasks become more complex, highlighting the growing importance of competence-based evaluations in fintech chatbot interactions.

Keywords: fintech chatbots; Generation Z; consumer experience; Expectation-Confirmation Model (ECM); Heuristic-Systematic Model (HSM); Stimulus-Organism-Response (SOR) theory



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1. Introduction

According to the Digital 2025 Global Overview Report published by We Are Social, a media network that has been operating since 2008 and regularly publishes global digital data, 5.56 billion of the world's 8.2 billion population use the internet, 5.24 billion people have created a social media profile, and internet usage among consumers aged 16–24 is 7 h and 35 min for men and 7 h and 11 min for women [1]. The same report also shows that the percentage of the population using the internet in Türkiye, where the study was conducted, is 88.3%, while those using mobile phones for internet access account for 96.9% of the population aged 16 and over who use the internet [1]. In today's digital world, where individuals spend a significant amount of time in online environments, companies place importance on providing 24/7 online services and maintaining effective communication with customers [2]. Furthermore, it has required adapting to changes in

customer expectations driven by technological developments [3]. One of the technologies companies use to enhance customer experience and maintain communication is artificial intelligence (AI) technology [4]. This technology enables companies to successfully participate in their marketing, production, and delivery processes [5,6]. Chatbots, which are artificial intelligence-based technologies with human-like characteristics, are programs that enable users to communicate digitally with a virtual entity to obtain information or entertainment [7]. In particular, AI-powered fintech chatbots used in digital and mobile banking represent a rapidly growing subset of these applications. Chatbots are software that enable personalized interactions with users by establishing human-like dialogues, and, particularly in the context of fintech and digital banking services, increase customer satisfaction with fast, automated responses [8]. Recent industry reports suggest that a substantial proportion of consumer–brand interactions are increasingly supported by chatbot technologies [9]. These robots can simulate natural language conversation by exchanging human-like text or speech (or both) as input and output [10]. Chatbots are widely used in frontline-stage business processes [11], on digital platforms and marketplaces [2], and in mobile applications [12]. Chatbots enhance the customer experience on the platforms where they are used and meet customer expectations through real-time interaction [13,14].

Artificial intelligence (AI) technology is becoming increasingly important in providing users with unique and personalized experiences in physical and digital environments [15]. At this point, AI chatbots are becoming increasingly widespread in marketing applications, enabling them to interact with customers like humans, thereby reducing customer calls and the resulting workload [4]. Statistics indicate that the chatbot market is experiencing rapid growth. The chatbot market, which continues to experience rapid growth in the customer service segment, is projected to grow at a compound annual growth rate (CAGR) of 23.3% between 2022 and 2030 [16]. From a sectoral perspective, investments in AI-powered fintech services and banking chatbots have been increasing rapidly. The projection that the global fintech market will grow by approximately 25 percent between 2022 and 2027 and reach 324 billion USD by 2026, together with the rise in the number of banking chatbot users in the United Kingdom from 1 million in 2020 to 7 million in 2023, indicates a fast-growing adoption of AI-driven solutions in financial services [17]. Previous studies on chatbots have primarily focused on identifying the motivational factors that influence users' continued use of this technology in their financial and service-related decision-making processes [15]. The algorithmic information processing systems of chatbots can contain cognitive and environmental cues similar to those found in financial advertisements [18], which can also influence users' perceptions of specific fintech-oriented chatbot functions [19]. Chatbots integrate various behavioral and psychological marketing elements to cater to customers at multiple stages of their financial purchasing journey, with human-like characteristics taking precedence [20].

Araujo [21] highlights two fundamental challenges in presenting chatbots, which are a type of disembodied conversational agent (DCA). First, since how chatbots are introduced to consumers and how they are framed (e.g., their human-like appearance) significantly influences consumer perceptions, designers and companies must present chatbots effectively in financial service contexts as well. Second, endowing chatbots with human-like characteristics (e.g., using a warm tone of voice or giving them a human-sounding name) affects consumers' perceptions of both the chatbot and the company using it, as well as their overall experience with the chatbot in fintech environments. To address these gaps, the current study incorporates the humanness features suggested by Dwivedi et al. [20], with particular reference to Yoganathan et al. [22]. The latter's work provides a foundational insight into the field by investigating the interplay of psychological cues within the financial customer journey. It highlights the importance of warmth and

competence transmission as key variables for assessing perceived humanness within social cognitive models.

However, not all customers interact with AI-powered online financial solutions in the same way, and Generation Z (those born between the mid-1990s and early 2010s) stands out as a distinct consumer group with unique behaviors [23]. It is well known that Generation Z is a tech-savvy group that frequently conducts digital banking activities, utilizes fintech applications, and possesses high levels of digital fluency and literacy [24]. Additionally, personalized financial assistants and chatbots have been found to enhance the user experience and boost Generation Z's confidence in financial decision-making [23]. Although previous studies have investigated the impact of chatbot quality on Generation Z in terms of the information and systems they provide [2,25], insufficient focus has been placed on researching the effects of fintech chatbot design, usability, and social interaction features within fintech contexts for Generation Z consumers, resulting in a significant gap in the literature.

Studies have found that Gen Z individuals have a limited ability to respond to complex financial queries when using chatbots and may even require human intervention and access to broader financial data [26]. Nevertheless, the impact of chatbots on consumers across generations is a topic worthy of further research [27]. The importance of focusing on millennials [28] and Gen Z [2] is also emphasized in the literature. Based on this, the manuscript aims to answer the following research questions:

- (i) How do specific features of AI-powered fintech chatbots in smartphone applications influence the internal perceptions of Generation Z users, and how do these perceptions shape the ultimate customer experience?
- (ii) How does the complexity level of the financial task Generation Z users interact with, the human-like features expected from an AI-powered fintech chatbot, and the influence of these features on the customer experience change?

To address these gaps, this study develops a framework that explains how the design, usability, and social interaction/human-like features (stimulus) of fintech chatbots used in smartphone applications influence customer experiences (responses) through the internal cognitive and affective states (organism) of Generation Z consumers. This framework (see Figure 1) integrates complementary models to uncover these relationships. First, we draw on the Stimulus-Organism-Response (S-O-R) model, which explains how environmental factors (stimulus) affect individuals' internal states (organism) and how this leads to behavioral outcomes (response). This model provides a suitable framework for understanding how AI-powered fintech and digital banking chatbots shape Gen Z's perceptions and emotional states (organism) toward financial customer experience (response) through stimulus. Second, we utilize the concepts of Social Interaction Characteristics and Humanness to examine the impact of chatbots' human-like characteristics and social interaction capabilities on user perceptions and experiences within financial service environments. In this form, the study contributes two critical insights to the literature.

The first contribution of this study is that it explains how heuristic cues derived from chatbot input factors shape users' initial perceptions of competence and warmth through the HSM (heuristic-systematic model). The current study uses HSM to explain how users form quick judgments in their initial interactions with fintech and banking chatbots [29]. HSM suggests that individuals use either a deep and analytical approach (systematic processing) or mental shortcuts and superficial cues (heuristic processing) when processing information. HSM can strike a balance between complexity and ease of application [30]. Especially in interactions that require quick evaluation, such as financial queries conducted via chatbots, users are likely to resort to heuristic processing to use their limited cognitive resources efficiently. Dogruel et al. [31] consider heuristic methods as cognitive shortcuts

adopted to reduce the complexity of computational tasks and decrease the use of resources such as cognitive activity and time. This aspect provides a legitimate basis for using HSM in the current study and aligns with expectations regarding the chatbot's response. The input factors in the model shown in Figure 1 are conceptualized as heuristic cues that enable users to form quick judgments about the chatbot's perceived competence (PC) and perceived warmth (PW), particularly in relation to financial task accuracy and interaction quality. This approach enables us to understand how chatbots' interface design, interaction style, and sense of social presence shape users' initial expectations regarding the chatbot's potential task effectiveness and helpfulness intent in financial service contexts before they engage in a deeper interaction. Therefore, using this model to examine the perceptions of Generation Z users of smartphone-based fintech applications that host chatbots sheds light on the psychological processes at the first point of contact and which specific design elements are practical in these processes.

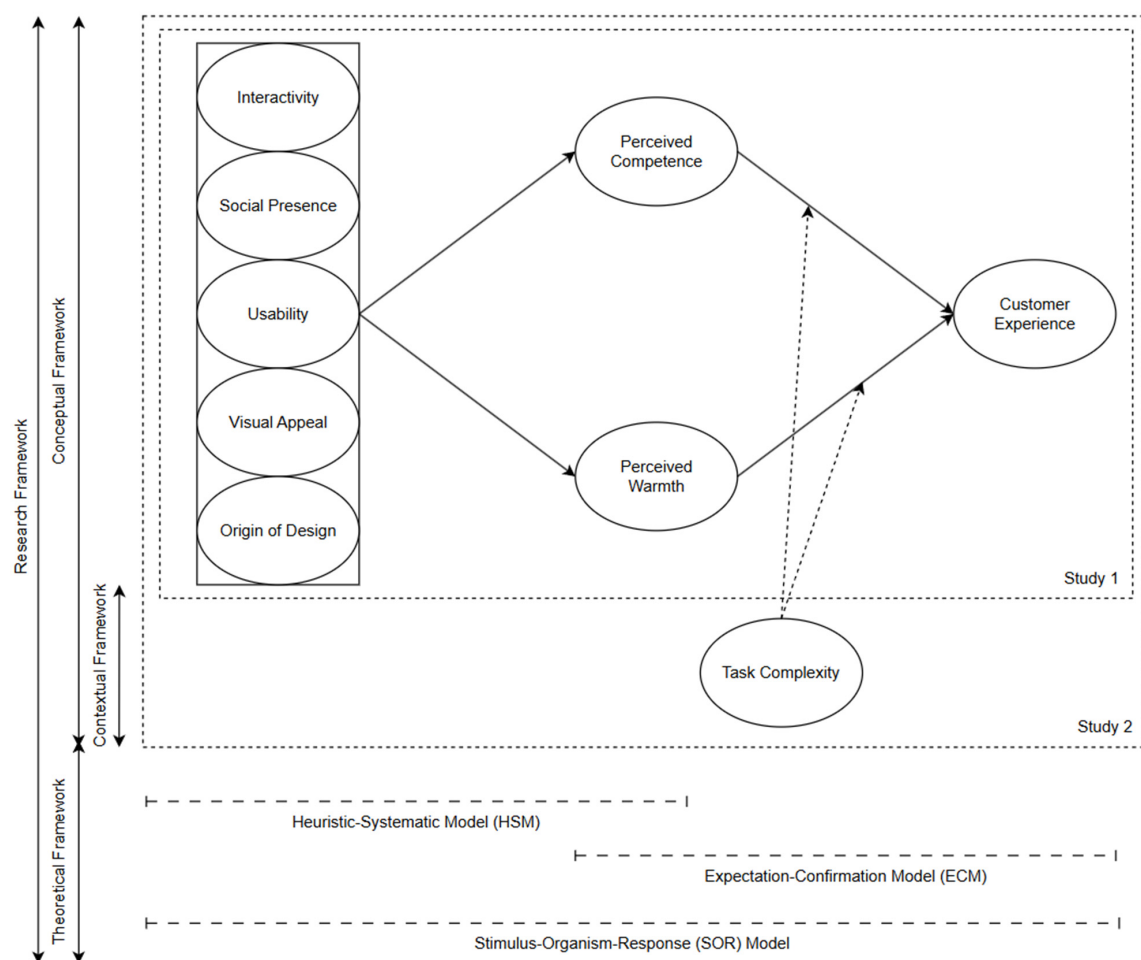


Figure 1. Research framework.

The present study provides a second significant contribution to the literature by integrating ECM [32,33] to explain how the customer experience is shaped after users interact with chatbots. ECM claims that satisfaction or overall experience evaluations are formed by comparing individuals' initial expectations for a product or service with the actual performance they experience. In accordance with ECM [34], it has been revealed that users' initial expectations of a service or product, and the extent to which these expectations are confirmed, significantly influence all subsequent interactions and their final perception of satisfaction. Alnaser et al. [35] emphasize that meeting expectations significantly af-

fects user satisfaction and experience in AI-supported financial services. By combining AI features with ECT, Bhatnagar & Rajesh [36] highlight AI's role in shaping young consumers' satisfaction and continuance intention in fintech ecosystems. The findings of the mentioned study confirm the strong effect of e-satisfaction on continuance intention in both generations, particularly among Generation Z. In the current study, perceived competence (PC) and perceived warmth (PW), generated by feeding the input variables specified in Figure 1 into the HSM, represent users' expectations for the chatbot's performance and interaction quality during financial tasks. After users interact with the chatbot, these initial expectations are compared with the chatbot's actual capabilities (e.g., understanding and resolving financial queries correctly) and interaction style (e.g., attitude toward the user). If the chatbot's performance meets or exceeds these expectations, positive validation and a positive customer experience are expected; otherwise, negative validation, disappointment, and a negative experience are anticipated. The use of this model in smart applications, particularly for chatbots and Generation Z, plays a crucial role in understanding the dynamics underlying post-use evaluations and the ultimate financial customer experience, extending beyond first impressions, and demonstrating how initial perceptions of perceived competence (PC) and perceived warmth (PW) influence this experience. Thus, the importance of creating an attractive, genuine, and trustworthy first impression in fintech-oriented chatbot design, as well as delivering performance that supports this impression, is emphasized for a holistic customer experience.

2. Theoretical Background

Stimulus-Organism-Response (S-O-R) Framework

The current study examines AI-powered fintech chatbots used in digital banking services, focusing on their social features, usability, and design dimensions from the perspective of Generation Z. We believe that the S-O-R framework will support the theoretical representation of the model applied in the study. First developed by Mehrabian & Russell [37] and modified by Jacoby [38], the S-O-R framework posits that external environmental variables encompassing auditory, visual, and olfactory stimuli (S) may influence individuals' internal cognitive processes, emotional states, and emotional responses (O), resulting in psychological tendencies or behavioral responses (R) [2,37,38]. Studies examining differences and changes in users' attitudinal and behavioral reactions about information systems frequently utilize the S-O-R framework [39].

Recent studies on AI chatbots and consumer behavior have found that the S-O-R framework provides a theoretical basis for understanding these interactions. For instance, Hwang & Kim [40] show that the core properties of financial chatbots, such as rapid response, transaction accuracy, and constant availability, significantly shape users' cognitive states (e.g., trust and perceived usefulness) and affective reactions (e.g., comfort and reduced stress), which in turn translate into higher satisfaction and continued usage intentions. Customer satisfaction with customer service [2], usage-based value co-creation [41], online purchase intent [42], and customer perception, response, experience, and adoption of online services [43–45] have been associated with chatbot AI, and the S-O-R framework has been preferred as the theoretical background. Furthermore, the literature indicates that the same theoretical framework is used in studies investigating customer engagement on online sharing and social media platforms [46] and online repurchase intention [47] based on artificial intelligence. Similarly, a study examining the effect of AI chatbots' human-like characteristics on the intention to switch to human agents through trust also employed the aforementioned framework [48]. The framework, which is described as a well-justified theoretical background in technology-related contexts [49], has been used as a model in studies focusing on different generations. The framework has been adopted as a theoretical

background for studies focusing on the quality of AI chatbots and their effects on Gen Z's satisfaction and advocacy [2], as well as on enhancing millennial consumers' experiences through social media marketing [28].

In the context of AI-powered fintech chatbots, the input variables of interactivity, social presence, usability, visual appeal, and design origin have been included as stimuli in the S-O-R-based model of the current study. Among social factors, interaction enhances users' sense of control and shapes their experience through the two-way communication established between chatbots and users [50]. Social presence creates the perception that someone is talking to the user, thereby making them feel at ease, depending on the chatbot's human-like qualities and attitudes [51]. When considering appearance factors, it is well understood that visual interface design serves as a visual stimulus that creates appeal and enhances the consumer experience [15]. Additionally, the perception of whether the design originates from a local or foreign source can affect users' trust and familiarity. Usability, another key factor, emphasizes the ease and accuracy of users' interactions with the chatbot interface, thereby shaping users' overall experience [52]. VakıfBank—ViBi, warmth and competence are two critical dimensions that determine humanness in social psychology [53]. Beyond being digital natives, Generation Z members are characterized as highly conscious and critical consumers who demand transparency and reliability in their financial dealings. For this cohort, technological fluency is accompanied by a heightened sensitivity to data security and ethical standards. Therefore, trust emerges as a pivotal element in the fintech context; without establishing a foundation of trust, the advanced functional features of AI chatbots may fail to convert into a sustained positive customer experience. Furthermore, in some studies on chatbots, these dimensions have been used as mediating variables to investigate the consumer purchase journey and chatbot experience [20,54]. In the current study, humanness factors were placed in the "organism" stage because they represent individuals' psychological, emotional, and cognitive states that are unique to each person [37]. Indeed, human characteristics endow chatbots with the ability to behave warmly and sincerely and to provide valid answers to questions asked [20]. Finally, customer experience encompasses the entire customer journey, from the first point of contact to all interactions experienced during a purchase [55]. Moreover, experience level is the cumulative result of all cognitive processes, emotional responses, and interactions that shape an online customer's perspective of a product or brand [56]. Therefore, in the present study, customer experience (CX) is considered as a Response element within the S-O-R framework.

3. Hypotheses Development

3.1. Usability (Us)

Usability (Us) is a characteristic that expresses the degree to which a human–computer interface can be used to effectively and efficiently achieve a defined goal, and it affects the digital customer experience [57,58]. According to [15], Us is one of the dimensions that should be prioritized in e-service environments. Consistent with this view, Rafiq et al. [44] find that perceived ease of use substantially improves users' attitudes toward chatbots, reduces their cognitive load, and positively shapes their overall service experience. In the context of digital banking, Ionaşcu et al. [59] further demonstrate that perceived ease of use, together with speed and security, strongly determines users' behavioral responses and overall customer experience in fintech services. Customers perceive companies that use chatbots on e-commerce sites as innovative because they can initiate conversations or demonstrate product or service functionality [60]. Chatbots can provide personalized communication tailored to customers' specific needs, thereby preventing additional complications and explaining the importance of reliability in addressing customer needs [60,61].

The literature suggests that a chatbot specifically designed for an individual's use has a positive effect on perceptions of warmth and competence [54]. To understand the effect of this low cognitive variable, we posit as follows:

H_{1(c)}. *Us positively affects PC.*

H_{2(c)}. *Us positively affects PW.*

3.2. Interactivity (In)

Interactivity (In), which refers to the level of interaction with the virtual service environment and chatbots, affects consumers' trust and experience with AI chatbots [62]. It is also defined as having high-speed response capabilities and being user-friendly in chatbots [63]. Achieving high In increases user adoption of chatbots and enhances their experience [21]. Empirical evidence in the financial services domain also suggests that chatbots' ability to provide instant responses and reduce waiting time enhances perceived interaction quality, thereby directly strengthening user satisfaction [40]. Highly interactive virtual environments tend to evoke positive emotions, such as enjoyment, curiosity, and excitement, among customers, whereas low-interactive environments can lead to indifference or boredom [15,64]. In addition, designs that increase and enhance the virtual experience [21,64]. Digital customers expect interactions with AI chatbots to reflect human-like characteristics [21] and to meet hedonic expectations, such as being designed to resemble human conversation [65]. To evaluate the effects of the relevant variable, we posit as follows:

H_{1(a)}. *In positively affects PC.*

H_{2(a)}. *In positively affects PW.*

3.3. Visual Appeal (VA)

According to Tran et al. [66], the aesthetic appeal of e-service environments is evaluated based on two factors: entertainment and visual appeal (VA). Indeed, VA, which is the first point of contact consumers have with a product, conveys the aesthetic appeal of the interface in e-service environments, and an interface designed in this direction provides a memorable user experience [64]. VA is the first step in a consumer's encounter with a technological product, leading them to associate the visual appearance of the product's interface with its usefulness and functional performance [67]. According to Kim [15], visually appealing chatbots increase user satisfaction and engagement, accompanied by positive emotions. Similarly, Rafiq et al. [44] report that well-structured and aesthetically pleasing chatbot interfaces foster more favorable user perceptions and increase the likelihood of technology adoption. To test the role of this variable on the research model, we posit as follows:

H_{1(d)}. *VA positively affects PC.*

H_{2(d)}. *VA positively affects PW.*

3.4. Social Presence (SP)

Social presence (SP) is the perception of an individual's digital or physical counterpart in interaction as a socially present, responsive, and interactive entity [68]. This perception creates the impression that a real social actor is present to the user and facilitates the attribution of human-like characteristics (anthropomorphic qualities) to this interlocutor [21].

In line with this, Wut et al. [69] demonstrate that incorporating human-like conversational style and socially oriented communication cues into chatbots increases users' perceived social presence and enhances their overall customer experience. Focusing on financial chatbots, Choi et al. [70] further confirm that a strong sense of social interaction and presence reinforces users' trust in chatbot-based services. SP, one of the human-like characteristics attributed to machines in human-machine interaction, plays a vital role in explaining the relationship between chatbots' social cues and users' social responses [71]. Furthermore, Klein et al. [72] have argued that a warm and highly interactive chatbot design can strengthen SP. There is a positive relationship between SP and the perceived humanness ratings of chatbots [73]. Hess et al. [74] also claimed that SP could convey a sense of warmth, sociability, and human touch with technology. To determine whether this variable had a significant effect, we posit as follows:

H_{1(b)}. *SP positively affects PC.*

H_{2(b)}. *SP positively affects PW.*

3.5. Originality of Design (OD)

Originality is a complex structure in human-artificial intelligence interaction, based on the collaboration between human creative intent and the productive capabilities of artificial intelligence [75]. The originality of design (OD), which expresses the chatbot interface's uniqueness and creativity, can increase user interest and satisfaction [15]. Arrighi et al. [76] have documented an initial phase in which industrial designers develop conceptual visions through drawings guided by a design brief. Building on this foundation, when examining chatbot usage and design origins, the OD for a chatbot can be expressed through a series of initial elements such as the fundamental problem definition established by its developers, the needs of the target user audience, the desired personality traits for the chatbot (e.g., helpful, humorous, formal), core functions, and the targeted user experience Bitner [77] XY emphasizes that OD features in physical service stores appeal to consumers' aesthetic perceptions Yadav & Mahara [78] highlights that aesthetic and layout perceptions of design in the e-service environment are strong determinants of purchase intention. Additionally, Kim [64] found that OD significantly reduced users' negative emotions but did not have a statistically significant effect on directly increasing positive emotions. Complementing these findings, Rafiq et al. [44] show that innovative and original design elements lead users to evaluate chatbots as "innovative" and "value-creating" services, thereby strengthening their acceptance and adoption intentions. The author also found that OD has a meaningful positive effect on users' behavioral intentions to continue using technology, albeit indirectly, through emotional responses and satisfaction. In this regard, it is thought that the interface and interactions provided by chatbots' OD may also function to reduce users' negative emotions, thereby indirectly and positively affecting their behavioral intentions.

The practical and positive perception of AI-powered chatbots by users is primarily related to PC and PW, which are fundamental dimensions that shape the perception of humanness [20,63]. As emphasized by Dwivedi et al. [20], these perceptions play a crucial role in shaping the chatbot experience and users' intentions to recommend. In this context, OD in chatbot interface and interaction design can be considered an essential factor that influences these fundamental perceptions of humanity. In line with the definitions provided by Kim [64], it is assumed that an innovative, fresh, or technologically advanced OD, resonating with the cognitive cues identified in the study by Dwivedi et al. [20], can reinforce the impression that the chatbot is more capable, intelligent, and able to perform its tasks effectively. To this end, we posit as follows:

H_{1(e)}. *OD positively affects PC.*

H_{2(e)}. *OD positively affects PW.*

3.6. Perceived Competence (PC)

Competence is the ability to adapt to changing conditions in the provision of services [53]. Research on automation reveals that robots demonstrating proficiency in manual tasks and interpersonal communication are viewed more positively by consumers [79]. The literature indicates that the use of AI-based service robots in hotels positively affects word-of-mouth communication and continued usage intentions [80]. Furthermore, it has been observed that the competence of AI-supported robots used in digital learning environments affects students' engagement levels [81]. It is known that AI chatbots with human-like characteristics increase their PC [54], and that PC, in turn, affects CX through perceived authenticity [82]. In addition, several studies in the literature have examined the intention to use AI chatbots in digital service environments, as well as loyalty and experience, and have also investigated the mediating role of PCs [20,53,54]. Extending these insights to financial services, Lam [83] demonstrates that in fintech settings, where financial transactions inherently carry high risk, users consistently prioritize technical competence over socio-emotional qualities and expect high accuracy, fast processing, and very low error tolerance from AI systems. Correspondingly, Mun & Kim [84] demonstrate that the performance of large language model-based decision aids in financial tasks directly shapes users' perceptions of system competence; higher accuracy and consistency increase cognitive trust and strengthen the overall customer experience. Moreover, Al-Daoud & Abu-AlSondos [85] demonstrate that users' trust in AI-driven financial services is primarily grounded in technical indicators of reliability, explainability, and error tolerance. This suggests that perceived competence becomes more salient than perceived warmth in fintech environments where AI-powered financial chatbots support high-stakes decision-making. To determine the explanatory and mediating power of this variable in the study, we posit as follows:

H₃. *PC positively affects CX.*

H_{5(a)}. *PC mediates the relationship between In and CX.*

H_{5(b)}. *PC mediates the relationship between SP and CX.*

H_{5(c)}. *PC mediates the relationship between Us and CX.*

H_{5(d)}. *PC mediates the relationship between VA and CX.*

H_{5(e)}. *PC mediates the relationship between OD and CX.*

3.7. Perceived Warmth (PW)

Perceived warmth (PW) refers to the consumer's level of perception of kindness and courtesy, which fosters stronger relationships and improves service quality, thereby affecting the individual's emotional value toward service delivery [53]. PW's AI-based service robots used in hotels have a positive effect on word-of-mouth communication and continued usage intent [80]. PW service delivery can yield various positive outcomes, including satisfaction, intention to continue using, and behavioral intentions, and has a direct effect on customer experience [20]. AI chatbots, which serve as frontline workers in e-service environments, can increase PW among users through simple human-like movements and

facial expressions [53] and facilitate interaction between individuals thanks to their social skills [86]. The literature also includes several studies on loyalty and experience with chatbots, which examine PW's mediating role [20,53]. However, Wut et al. [69] report that, in financial chatbot settings, perceived warmth has only a limited effect on service evaluations and customer experience, as users tend to prioritize technical capacity over socio-emotional qualities during financial decision making. To test the direct and/or indirect effect of the relevant variable on the dependent variable, we posit as follows:

H₄. *PW positively affects CX.*

H_{6(a)}. *PW mediates the relationship between In and CX.*

H_{6(b)}. *PW mediates the relationship between SP and CX.*

H_{6(c)}. *PW mediates the relationship between Us and CX.*

H_{6(d)}. *PW mediates the relationship between VA and CX.*

H_{6(e)}. *PW mediates the relationship between OD and CX.*

3.8. Customer Experience (CX)

Customer experience (CX) is the sum of perceptions and evaluations that result from a customer's interactions with a brand, creating a positive impression of both the purchasing process and the brand itself [87,88]. In this study, customer experience was selected as the primary response variable rather than customer satisfaction due to its holistic and multidimensional nature. While satisfaction often refers to a post-purchase evaluative judgment, customer experience encompasses the user's immediate cognitive, emotional, and sensory reactions during the interaction. Within the S-O-R framework, CX serves as a more comprehensive 'Response' that captures the direct impact of stimuli on the organism's internal state, reflecting the continuous journey of Generation Z within the fintech ecosystem rather than a singular outcome of satisfaction. Puertas et al. [8] further articulate CX as a comprehensive subjective response, a synthesis of emotions, perceptions, and attitudes arising from a customer's holistic engagement with an organization, encompassing its personnel, procedures, and, critically, its digital technologies. They underscore that this experience is inherently multidimensional, combining cognitive facets such as the quality of information and functional utility with affective dimensions, including the enjoyment derived from these interactions, particularly within the online environment. The increasing difficulty of providing high-quality service to customers in the evolving online environment has necessitated better CX [60] and human–robot interactions that establish secure relationships [5]. The use of artificial intelligence technologies in service environments enhances the overall service experience [5] and fosters customer loyalty [46]. In the fintech domain, Hwang & Kim [40] empirically show that financial chatbots improve the customer experience by increasing service speed, transaction accuracy, and accessibility, thereby elevating satisfaction and continuance intention. Choi et al. [70] further emphasize that customer experience with financial chatbots is primarily shaped by perceived service quality, interaction level, and trust in the chatbot's recommendations. Supporting these findings, Akdemir & Bulut [89] show that chatbot communication quality is a key antecedent of user satisfaction and that satisfaction has a more substantial effect on chatbot reuse intention than on online purchase intention. In the present study, CX specifically refers to Generation Z users' holistic evaluations of their interactions with AI-powered fintech chatbots embedded in mobile banking applications. One such technology is AI

chatbots, which simulate human-to-human communication and operate based on natural language processing. This topic has been extensively researched in the literature for its direct and indirect effects on CX [9,60].

The ability to store large volumes of customer data and adapt functionality based on previous interactions makes these bots a crucial actor in creating a positive CX [90]. Chung et al. [13] argue that chatbots are an effective tool for increasing customer engagement and providing flexible and customizable digital services, and that online communication history could contribute to personalized product development processes in the future. It is well established that the human-like interaction styles and conversation-response types employed by customer service chatbots affect users' experiences [91]. Additionally, CX is influenced by chatbots' Us [60], problem-solving ability [91], proactive response generation level [27], information quality [92], PC, and PW [20].

3.9. Moderating Role Task Complexity

Customer service on e-commerce platforms is expected to assist customers throughout their entire digital journey. While consumers value comprehensive information, the assimilation of more data requires consumers to use additional cognitive resources to reach a definitive purchasing decision, which can ultimately lead to cognitive overload for online consumers [93]. Morgeson & Humphrey [94] point out that complex tasks typically require multiple high-level skills and are mentally more demanding and challenging. According to Wang et al. [95], one factor influencing consumer attitudes in online service environments is the complexity of the tasks performed by fintech chatbots, which moderates the relationship between the communication style established with consumers and the cognition-based trust it creates. Consistently, Choi et al. [70] report that, in financial chatbot services, expectations regarding performance and reliability become particularly salient in complex tasks such as verification, document classification, and transaction monitoring, making technical competence a critical evaluation criterion. Indeed, Xu et al. [96] observed that perceptions of artificial intelligence's problem-solving abilities decrease when task complexity (TC) increases. TC negatively affects trust and satisfaction, while short-step dialogues are perceived as less complex even if they take longer [97]. Therefore, while users prefer fintech chatbots for simple information exchange, it has been observed that a conversational style weakens trust in complex tasks, and a goal-oriented communication style is more widely adopted [98].

Some studies in the literature have investigated the moderating effect of TC on the relationship between augmented reality-supported product presentation and experience-based value perception [99] and on the relationship between augmented reality and consumer responses in a mobile shopping environment [100]. This finding reveals that TC has been incorporated into the research model to enhance understanding of CX with AI-powered fintech chatbots in digital banking environments. In the relationship between AI-supported online customer service and perceived problem-solving ability and usage intention [96], as well as in the relationship between AI chatbots' human-like characteristics, such as empathy and friendliness, and the trust placed in them [101], TC played a moderating role. Cheng et al. [101] also included this moderator in their model designed to investigate trust in chatbots within the S-O-R framework. It was also found that TC moderates the relationship between chatbot communication styles (task- or social-oriented) and user trust [98]. Likewise, Wut et al. [69] note that as TC increases, chatbots may reach the limits of their problem-solving capabilities, prompting the need to escalate to human agents and underscoring TC's moderating role in the relationship between system performance and customer experience. Therefore, the moderating effect of TC has been included in the research model to better understand CX with AI chatbots. To understand the moderate

effect of this variable on the relationship between the O-R layers and the indirect effect on the S-O-R layers, we posit as follows:

H₇. *TC moderates the association of PC on CE.*

H₈. *TC moderates the association of PW on CE.*

H_{9(a,b,c,d,e)}. *PC mediates the effect of Stimulus Variables on CX. Moreover, TC moderates this mediating effect, such that the positive relationship between PC and CX becomes stronger as TC increases. (a: In, b: SP, c: Us, d: VA, e: OD).*

H_{10(a,b,c,d,e)}. *PW mediates the effect of Stimulus Variables on CX. Moreover, TC moderates this mediating effect, such that the positive relationship between PW and CX becomes weaker as TC increases. (a: In, b: SP, c: Us, d: VA, e: OD).*

4. Study 1

4.1. Objective and Overview

Study 1 investigates the fundamental effects of specific AI-powered chatbot features on the CX of Generation Z users. Within the scope of the study, participants were introduced to an AI-powered chatbot and provided basic usage examples (including question-and-answer cycles and menu navigation). The primary objective of this research, conducted with Generation Z participants, is to examine how chatbot features (Stimulus) shape users' perceptions (Organization) during interaction and how these perceptions determine the post-interaction CX (Response), thereby testing H₁, H₂, H₅, H₆ (and a, b, c, d sub-hypotheses) and hypotheses H₃ and H₄.

4.2. Methods

4.2.1. Scales

The survey presented to participants was developed using scales with established validity and reliability in literature. The dimensions of Us, In, VA, and OD were measured using statements adapted from Kim [15]. The SP dimension was adapted from Araujo [21]. The PC and PW measurements of the participants were taken from an explanatory study by Dwivedi [20]. Although there are various studies in literature on the CX dimension, the statements from Puertas et al. [8] were selected as the most relevant to this study. Finally, the TC dimension was adapted from Morgeson & Humphrey [94]. All scale items were measured using 5-point Likert statements ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

4.2.2. Participants and Sampling

One hundred sixty-six people participated in the study. The average age of the participants was 22.65 ± 3.01 (18–28), and the gender ratio was calculated as $n_{\text{Female}} = 119$ (71.7%) and $n_{\text{Male}} = 47$ (28.3%). It is noteworthy that the majority of participants were single ($n_{\text{single}} = 139$, 83.7%; $n_{\text{married}} = 27$, 16.3%). Educational attainment was categorized into six different levels, but a significant majority (92.2%) held high school (41.6%), associate's degree (33.7%), and bachelor's degree (16.9%) qualifications. When annual household incomes were calculated, they were distributed as follows: \$1029.34 and below (56.6%), \$1029.36–\$2058.67 (38.0%), and \$2058.70 and above (5.4%) (1\$ = 38.8 TL). Finally, all participants reported conducting financial transactions via mobile banking applications; however, none reported prior interaction with AI-powered chatbots integrated into these platforms.

Participants consist of individuals residing in Türkiye. Data was collected through electronic surveys administered via Google Forms between October 2024 and February 2025. For this study, convenience sampling was preferred due to economic and accessibility concerns. Participants were screened based on two primary inclusion criteria: (a) possession of an active mobile banking application installed on their smartphones, and (b) no prior interaction with the AI-powered virtual assistants embedded within these applications. To validate the first criterion, participants' devices were physically inspected with their explicit consent. Subsequently, as part of the study protocol, participants were instructed to access the conversational AI interface within their banking app and initiate financial interaction. The interaction session was designed to last approximately 10 to 15 min, ensuring sufficient depth for users to evaluate the system's performance. Participants were required to complete a series of structured tasks, including checking account balances, inquiring about credit card limits, and asking for exchange rate information. This multi-task approach allowed users to experience various conversational flows, ranging from simple command-based responses to more complex inquiry-driven dialogues. If they could not find the chatbot in the application or did not understand its purpose, these volunteers were included in Study 1; otherwise, they were excluded. Volunteers who met both conditions were considered participants. Control questions were included to ensure that responses to the questionnaire were consistent and carefully considered. Non-systematic intervals were added to the questionnaire form with the question "If you are reading this question, you have only five fingers. Otherwise, check strongly disagree" and "If you are reading this question, you can fly. Otherwise, check 'Strongly disagree'." Finally, no incentives were promised or offered to the volunteers for their participation.

4.2.3. Analysis

Structural Equation Modeling (SEM) was used to test the hypothesized relationships in this study. Before the analysis, the distributions of the variables were examined, and it was determined that the normality assumption was not met based on the results of the Kolmogorov–Smirnov Z test applied to samples larger than 50 ($p < 0.05$). Due to the non-normal distributions [102] recommend the PLS-SEM approach. Similarly, given the complexity of the structural model and the study's aim to test the theoretical framework, it is evident that PLS-SEM is the most appropriate approach [103]. PLS-SEM analyses were conducted using SmartPLS v 4.1.0.1 software. In the PLS-SEM approach, the analysis is typically conducted in two stages. First, the measurement model (external model) is evaluated for validity and reliability, followed by an examination of the structural model (internal model) and the hypothesized relationships. The main reasons for choosing this approach include (i) its ability to successfully model the numerous latent variables in our study and the complex and intertwined relationships between them, and (ii) its ability to comprehensively assess the consistency of the structural relationships we hypothesized with empirical data. Additionally, potential indirect (mediating) effects were tested using bootstrapping.

4.3. Results

4.3.1. Measurement Model Assessment

With the measurement model created, the reliability and validity results of the constructs used in the research were tested. The software calculated model fit measures as SRMR = 0.060, $\chi^2 = 1635.209$, $\chi^2/df = 2.67$, NFI = 0.714. Finally, GoF = 0.629 (goodness of fit) indicates that the model fit is "very good" [102,104]. The results of the Squared Euclidean Distance = 2.553 (d_ULS) and the Geodesic Distance = 1.935 (d_G) calculated for this purpose indicate that the validity of the model is ensured ($p > 0.05$) [105,106]. In

this study, factor analysis was used to evaluate the internal consistency, reliability, and increasing discriminant validity of the structures. Factor loadings and average variance extracted (AVE = Average Variance Extracted) coefficients of the statements measuring the constructs were calculated for incremental validity. Cronbach's Alpha and composite reliability (CR) were used to assess internal consistency. As stated by Hair et al. [107,108], acceptable threshold values are ≥ 0.70 for factor loadings and Cronbach's Alpha/CR coefficients, and ≥ 0.50 for AVE values. The results of the measurement model for the variables (values without brackets) are presented in Table 1.

Table 1. Measurement model statistics for convergent validity and internal consistency (reliability) assessment.

Construct and Item	Convergent Validity		Internal Consistency/ Reliability	
	Outer Loading	AVE ^a	α ^b	ρ ^c
Interactivity (In)		0.644 (0.765)	0.816 (0.898)	0.878 (0.940)
In1	0.765 (0.873)			
In2	0.792 (0.884)			
In3	0.847 (0.881)			
In4	0.804 (0.861)			
Social Presence (SP)		0.718 (0.782)	0.870 (0.907)	0.911 (0.935)
SP1	0.878 (0.872)			
SP2	0.862 (0.891)			
SP3	0.801 (0.892)			
SP4	0.847 (0.882)			
Usability (Us)		0.683 (0.706)	0.922 (0.930)	0.938 (0.944)
Us1	0.875 (0.881)			
Us2	0.817 (0.875)			
Us3	0.860 (0.849)			
Us4	0.852 (0.821)			
Us5	0.857 (0.794)			
Us6	0.775 (0.861)			
Us7	0.738 (0.795)			
Visual Appeal (VA)		0.708 (0.753)	0.862 (0.890)	0.906 (0.924)
VA1	0.832 (0.840)			
VA2	0.851 (0.883)			
VA3	0.859 (0.910)			
VA4	0.822 (0.837)			
Originality of Design (OD)		0.690 (0.732)	0.850 (0.878)	0.899 (0.916)
OD1	0.814 (0.855)			
OD2	0.872 (0.882)			
OD3	0.768 (0.830)			
OD4	0.864 (0.855)			
Perceived Competence (PC)		0.715 (0.724)	0.920 (0.923)	0.938 (0.929)
Co1	0.785 (0.707)			
Co2	0.867 (0.849)			
Co3	0.806 (0.888)			
Co4	0.862 (0.895)			
Co5	0.864 (0.884)			
Co6	0.885 (0.870)			
Perceived Warmth (PW)		0.730 (0.723)	0.877 (0.872)	0.915 (0.912)
Wa1	0.810 (0.784)			
Wa2	0.878 (0.882)			
Wa3	0.841 (0.863)			
Wa4	0.886 (0.869)			

Table 1. *Cont.*

Construct and Item	Convergent Validity		Internal Consistency/ Reliability	
	Outer Loading	AVE ^a	α ^b	ρ ^c
Customer Experience (CX)		0.786 (0.762)	0.909 (0.895)	0.936 (0.927)
CE1	0.864 (0.906)			
CE2	0.901 (0.888)			
CE3	0.926 (0.887)			
CE4	0.854 (0.807)			
Task Complexity (TC)		- (0.780)	- (0.859)	- (0.914)
TC1	- (0.902)			
TC2	- (0.891)			
TC3	- (0.855)			

Notes: The values are presented for Study 1 (without brackets) and Study 2 (with brackets), respectively. ^a: Average variance extracted, ^b: Cronbach's alpha, ^c: Composite reliability. -: Shows model with no task complexity.

The analyses revealed that the α coefficients of the structures ranged from 0.816 to 0.922, while the ρ coefficients ranged from 0.878 to 0.938. These findings indicate that the scales have high structural reliability. The factor loadings ranged from 0.738 to 0.926, and the AVEs ranged from 0.644 to 0.786, providing evidence of the measurement model's convergent validity. The Heterotrait–Monotrait Ratio of Correlations (HTMT) criterion proposed by was used to determine the discriminant validity. The HTMT statistics developed by Henseler et al. [109] were used to assess whether the model structures could be successfully distinguished from one another (discriminant validity). The HTMT coefficients, as determined by the analysis results, are presented in Table 2.

Table 2. Discriminant validity assessment (Study 1).

Construct	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Interactivity (In)	0.802							
(2) Social Presence (SP)	0.509 (0.596)	0.847						
(3) Usability (Us)	0.696 (0.800)	0.547 (0.607)	0.826					
(4) Visual Appeal (VA)	0.532 (0.631)	0.470 (0.535)	0.681 (0.762)	0.841				
(5) Originality of Design (OD)	0.703 (0.838)	0.618 (0.719)	0.755 (0.849)	0.708 (0.820)	0.830			
(6) Perceived Competence (PC)	0.625 (0.713)	0.676 (0.746)	0.671 (0.725)	0.624 (0.699)	0.747 (0.837)	0.846		
(7) Perceived Warmth (PW)	0.455 (0.537)	0.473 (0.534)	0.538 (0.595)	0.629 (0.717)	0.574 (0.658)	0.632 (0.704)	0.855	
(8) Customer Experience (CX)	0.616 (0.713)	0.612 (0.685)	0.717 (0.780)	0.637 (0.716)	0.703 (0.798)	0.714 (0.777)	0.680 (0.759)	0.887

Notes: The values are presented for $\sqrt{\text{AVE}}$ (without brackets) and HTMT (with brackets), respectively.

4.3.2. Structural Model Assessment

Following the reliability and validity analyses of the structures, structural model analysis was performed to reveal the causal relationships between them. To detect common method bias, a VIF-based multicollinearity analysis was performed [110]. VIF values were checked with respect to the endogenous constructs (PC, PW, and CE) and ranged from 1.665 to 3.511. The outer values ranged from 1.667 to 3.751. At the same time, according to the Harman single-factor test, the statements are combined into four factors. The first factor

explains approximately 48.504% of the total variance. These results indicate that common method variance is not a significant problem in the present study.

The results (Table 3 values without brackets) showed that SP ($\beta = 0.306, p = 0.008$) and Original Design ($\beta = 0.307, p = 0.020$) variables have a positive and significant effect on PC. So $H_{1(b)}$ and $H_{1(e)}$ were supported. In addition, the VA variable ($\beta = 0.393, p = 0.006$) has a positive and significant effect on PW ($H_{2(d)}$: Supported). PC ($\beta = 0.470, p = 0.001$) and PW ($\beta = 0.386, p = 0.003$) affect CX positively. As a result of the analysis, hypotheses investigating direct effects ($H_{1(a),(c),(d)}$; $H_{2(a),(b),(c),(e)}$) were not supported. When indirect effects were examined, the paths of $SP \rightarrow PC \rightarrow CX$ ($\beta = 0.140, p = 0.020$) and $VA \rightarrow PW \rightarrow CX$ ($\beta = 0.143, p = 0.009$) were statistically significant. According to indirect effect results, $H_{5(a),(c),(d),(e)}$ and $H_{6(a),(b),(c),(e)}$ hypotheses were not supported.

Table 3. Hypotheses testing.

Effect	Hypotheses	Path	β	t	p Values	Sig.
Direct	$H_{1(a)}$	In $\rightarrow$ PC	0.114 (0.210)	1.270 (3.478)	0.204 (0.001)	No (Yes)
	$H_{1(b)}$	SP $\rightarrow$ PC	0.306 (0.103)	2.637 (1.327)	0.008 (0.184)	Yes (No)
	$H_{1(c)}$	Us $\rightarrow$ PC	0.102 (0.329)	1.022 (3.436)	0.307 (0.001)	No (Yes)
	$H_{1(d)}$	VA $\rightarrow$ PC	0.129 (0.213)	1.559 (3.389)	0.119 (0.001)	No (Yes)
	$H_{1(e)}$	OD $\rightarrow$ PC	0.307 (0.095)	2.319 (1.045)	0.020 (0.296)	Yes (No)
	$H_{2(a)}$	In $\rightarrow$ PW	0.044 (0.081)	0.339 (1.412)	0.735 (0.158)	No (No)
	$H_{2(b)}$	SP $\rightarrow$ PW	0.157 (0.110)	1.478 (1.339)	0.139 (0.180)	No (No)
	$H_{2(c)}$	Us $\rightarrow$ PW	0.060 (0.252)	0.539 (2.445)	0.590 (0.015)	No (Yes)
	$H_{2(d)}$	VA $\rightarrow$ PW	0.393 (0.468)	2.730 (5.568)	0.006 (<0.001)	Yes (Yes)
	$H_{2(e)}$	OD $\rightarrow$ PW	0.127 (−0.009)	0.737 (0.109)	0.461 (0.913)	No (No)
	H_3	PC $\rightarrow$ CX	0.470 (0.470)	3.465 (4.930)	0.001 (<0.001)	Yes (Yes)
	H_4	PW $\rightarrow$ CX	0.386 (0.320)	3.002 (3.637)	0.003 (<0.001)	Yes (Yes)
Indirect	$H_{5(a)}$	In $\rightarrow$ PC $\rightarrow$ CX	0.053 (0.099)	1.202 (0.045)	0.229 (0.175)	No (No)
	$H_{5(b)}$	SP $\rightarrow$ PC $\rightarrow$ CX	0.140 (0.048)	2.321 (−0.015)	0.020 (0.143)	Yes (No)
	$H_{5(c)}$	Us $\rightarrow$ PC $\rightarrow$ CX	0.055 (0.155)	0.859 (0.059)	0.390 (0.289)	No (No)
	$H_{5(d)}$	VA $\rightarrow$ PC $\rightarrow$ CX	0.062 (0.100)	1.363 (0.047)	0.173 (0.173)	No (No)
	$H_{5(e)}$	OD $\rightarrow$ PC $\rightarrow$ CX	0.143 (0.045)	1.934 (−0.027)	0.053 (0.152)	No (No)
	$H_{6(a)}$	In $\rightarrow$ PW $\rightarrow$ CX	0.018 (0.026)	0.313 (−0.008)	0.754 (0.076)	No (No)
	$H_{6(b)}$	SP $\rightarrow$ PW $\rightarrow$ CX	0.061 (0.035)	1.236 (−0.011)	0.216 (0.107)	No (No)
	$H_{6(c)}$	Us $\rightarrow$ PW $\rightarrow$ CX	0.030 (0.081)	0.455 (0.018)	0.649 (0.188)	No (No)
	$H_{6(d)}$	VA $\rightarrow$ PW $\rightarrow$ CX	0.143 (0.150)	2.611 (0.066)	0.009 (0.240)	Yes (No)
	$H_{6(e)}$	OD $\rightarrow$ PW $\rightarrow$ CX	0.053 (−0.003)	0.640 (−0.055)	0.522 (0.058)	No (No)

Notes: The values are presented for Study 1 (without brackets) and Study 2 (with brackets), respectively.

4.4. Discussion of Study 1

Study 1 investigated the relationship between AI-powered financial assistant features and Gen Z users' perceptions and their overall CX. The results demonstrate that the assistant's SP variable has a positive and significant effect on the PC variable, indicating that higher social presence leads users to appraise the financial AI as more competent. The positive and significant effect of the OD variable on the PC variable suggests that the Originality of Design contributes to users perceiving the assistant as more capable. Similarly, the positive and significant effect of the VA on PW indicates that the VA of the interface contributes to users perceiving it as more friendly and approachable. Consequently, driven by the mediating effects of PC and PW, the more competent and friendly users perceive the financial assistant to be, the more positive their CX.

The existence of indirect effects in the model is a significant finding that demonstrates the social dimension of the AI-powered financial assistant is intertwined with perceptions of competence. In contrast, the aesthetic dimension is intertwined with the PW, shaping the final experience. Some variables in the stimulus layer (In and Us) do not appear to directly or indirectly affect CX through the mediating variables (PC and PW) specified

in this model. This suggests that the effects of these factors on CX may emerge through different mediators or under various conditions (e.g., when moderators such as TC in financial transactions come into play). Therefore, examining these moderating effects in Study 2 becomes even more critical.

5. Study 2

5.1. Objective and Overview

Study 2 validates the findings of Study 1, providing a deeper insight into the relationships between user perceptions and CX (H_1 , H_2 , H_3 , H_4 , H_5 , H_6 , H_7) and extends the study by incorporating the TC variable (H_8 , H_9). Instead of users unfamiliar with fintech chatbots, participants in Study 2 received training on chatbot usage and had the opportunity to practice using them.

5.2. Methods

5.2.1. Scales

To ensure consistency, the same survey was conducted in Study 2. However, in this study, a special preparation and standardization process was implemented to deeply examine the role of TC, a moderating variable in the model. Before commencing the main study, all participants were instructed on how to use an AI-powered financial assistant and were allowed to practice independently. The participants' performance in both the learning and application steps was observed, and their suitability for participation in the study was confirmed. This process ensured that participants had the basic skills to interact with the financial assistant, thereby enabling a more accurate examination of the effects of different TC levels and the user's previous experience on the relationships among financial assistant features, user perceptions, and CX.

5.2.2. Participants and Sampling

One hundred ninety-five people were included in Study 2. The average age of participants was 22.71 ± 3.11 (18–28), and the gender ratio was $n_{\text{Female}} = 128$ (65.6%), $n_{\text{Male}} = 67$ (34.4%). It is noteworthy that most participants were single ($n_{\text{single}} = 172$, 88.2%; $n_{\text{married}} = 23$, 11.8%). Educational attainment was categorized into six different levels; however, the majority (94.9%) held high school (35.4%), associate's degree (39.5%), or bachelor's degree (20.0%) qualifications. When annual household incomes were calculated, they were distributed as follows: \$1029.34 and below (61.0%), \$1029.36–\$2058.67 (30.8%), and \$2058.70 and above (8.2%) (1\$ = 38.8 TL).

All consumers participating in this study were introduced to ViBi, an AI-powered digital financial assistant developed by VakıfBank (one of Türkiye's largest state-owned commercial banks) to provide digital support to its customers. The features of this financial assistant were introduced, and participants were asked to practice using it according to their own needs (money transfers, credit card payments, investment inquiries, account balance checks, security and information updates, etc.). During the training, the assistant's visual appearance and messages were shown to the participants. The assistant training and practice were conducted exclusively through the mobile banking application. To ensure transparency, participants were also informed about the research objectives. As in the previous study, no incentives were offered to participants. The survey was conducted similarly, including control questions.

5.2.3. Analysis

The techniques used in Study 1 were also used in the analysis phase. In this study, the Kolmogorov–Smirnov analysis was performed because $n > 50$, and it was calculated that

the variables did not follow a normal distribution. Similar reasons in Study 1 indicated that PLS-SEM was also the most appropriate approach in this study. The same two-stage PLS-SEM analyses were performed for Study 2, and moderator effects were also examined.

5.3. Results

5.3.1. Measurement Model Assessment

To validate the findings of Study 1, the measurement model of Study 2 was tested using the procedures and criteria outlined earlier. The results presented in Table 1 demonstrate that the model possesses robust psychometric properties. All factor loadings, reliability coefficients (Cronbach's Alpha and CR), and AVE values exceeded the recommended threshold values. Additionally, the model's overall fit was found to be adequate (SRMR = 0.060, $\chi^2 = 1801.768$, $\chi^2/df = 2.52$, NFI = 0.764, GoF = 0.696, $d_ULS = 2.957$, $d_G = 1.702$), thereby ensuring the model's robustness.

The evaluation of the measurement model began with an examination of the internal consistency reliability of the structures (Table 1 values in brackets). The observed Cronbach's Alpha (0.859–0.930) and Composite Reliability (0.912–0.944) coefficients are well above the accepted threshold values for all structures, indicating strong internal consistency. Next, convergent validity was addressed; all factor loadings (0.707–0.910) and AVE values (0.706–0.782) were found to meet the target levels. Finally, discriminant validity was assessed using the HTMT criterion developed by Henseler et al. [109] to test the uniqueness of the structures. As detailed in Table 1, the HTMT results confirmed that the model possesses discriminant validity.

The final check of discriminant validity was performed using the Heterotrait-Monotrait Ratio (HTMT). HTMT is the ratio of the average correlation of statements with different structures to the geometric mean of the correlations of statements with the same structure [109]. The researchers indicate that a ratio below 0.85 is a reliable indicator of discriminant validity. The results of our study are entirely consistent with this criterion. As shown in Table 4, all calculated HTMT coefficients are below the threshold value, confirming that each construct is unique and distinct from the others in the model.

5.3.2. Structural Model Assessment

After confirming the validity and reliability of the measurement model, the structural model was evaluated to test the relationships between the constructs. However, before conducting hypothesis tests, two necessary preliminary tests were performed that could weaken the reliability of the results: multicollinearity and common method bias. First, multicollinearity was examined using the Variance Inflation Factor (VIF) values [110]. VIF values below 5 indicate that there is no serious multicollinearity problem in the model. The analysis results showed that both the VIF values calculated for the internal structures (PC, PW, and CX) (range: 1.208–3.545) and the external VIF values (range: 1.582–4.490) were well below this threshold. Secondly, the risk of common method variance was assessed using Harman's single-factor test. The test results showed that all statements were separated into five distinct factors, with the first factor accounting for only 45.913% of the total variance. This ratio, being below the critical threshold of 50%, indicates that common method variance does not pose a significant issue for this study. Based on the positive results of these two tests, the structural model analysis continued with confidence.

The results indicate that in ($\beta = 0.210$, $p = 0.001$), Us ($\beta = 0.329$, $p = 0.001$), and VA ($\beta = 0.213$, $p = 0.001$) variables have a positive and significant effect on PC variables. So, $H_{1(a)}$, $H_{1(c)}$ and $H_{1(d)}$ hypotheses were supported. Additionally, Us ($\beta = 0.252$, $p = 0.015$) and VA ($\beta = 0.468$, $p < 0.001$) variables have a positive and significant effect on the PW variable. ($H_{2(c)}$, $H_{2(d)}$: Supported). PC ($\beta = 0.470$, $p < 0.001$) and PW ($\beta = 0.320$, $p < 0.001$)

variables have a positive effect on the CX variable. As a result of the analysis, hypotheses ($H_{1(b),(e)}$; $H_{2(a),(b),(e)}$) were not supported. When indirect effects were examined, unlike Study1, no hypothesis was supported ($H_{5(a),(b),(c),(d),(e)}$ and $H_{6(a),(b),(c),(d),(e)}$). The results obtained by examining the structure in Study 1 in a similar manner are presented in Table 3.

Table 4. Discriminant validity assessment (Study 2).

Construct	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Interactivity (In)	0.875									
(2) Social Presence (SP)	0.595 (0.655)	0.884								
(3) Usability (Us)	0.732 (0.799)	0.694 (0.753)	0.840							
(4) Visual Appeal (VA)	0.552 (0.616)	0.570 (0.632)	0.702 (0.771)	0.868						
(5) Originality of Design (OD)	0.639 (0.717)	0.749 (0.840)	0.726 (0.802)	0.636 (0.717)	0.856					
(6) Perceived Competence (PC)	0.691 (0.760)	0.649 (0.706)	0.773 (0.831)	0.679 (0.745)	0.681 (0.754)	0.851				
(7) Perceived Warmth (PW)	0.584 (0.651)	0.594 (0.654)	0.710 (0.776)	0.747 (0.840)	0.606 (0.683)	0.741 (0.809)	0.850			
(8) Customer Experience (CX)	0.623 (0.693)	0.706 (0.784)	0.758 (0.829)	0.711 (0.792)	0.679 (0.765)	0.751 (0.822)	0.721 (0.807)	0.873		
(9) Task Complexity (TC)	0.314 (0.355)	0.307 (0.344)	0.359 (0.399)	0.382 (0.439)	0.316 (0.363)	0.376 (0.419)	0.362 (0.418)	0.391 (0.440)	0.883	
(10) (6) $\times$ (9)	- (0.138)	- (0.070)	- (0.176)	- (0.243)	- (0.118)	- (0.317)	- (0.328)	- (0.274)	- (0.133)	
(11) (7) $\times$ (9)	- (0.227)	- (0.091)	- (0.281)	- (0.242)	- (0.189)	- (0.307)	- (0.432)	- (0.328)	- (0.079)	- (0.822)

Notes: The values are presented for $\sqrt{\text{AVE}}$ (without brackets) and HTMT (with brackets), respectively. -: Shows model with no task complexity.

In Study 2, the moderating effect of the TC variable was investigated. The effect of the moderate variable at +1 SD, Mean, and -1 SD levels was examined. The moderating effects on the direct effect between variables in the Organism and Response layers, as well as on the indirect effect in the Stimulus, Organism, and Response layers, were measured and evaluated (Table 5).

It has been calculated that the TC variable regulates the direct effect between the PC and PW variables, as well as the CX variable. A positive and statistically significant moderating effect of TC at all levels (+1 SD: $\beta = 0.523$, $p = 0.001$; Mean: $\beta = 0.470$, $p < 0.001$; -1 SD: $\beta = 0.417$, $p = 0.001$) on the relationship between PC and CX has been calculated (H_7 Supported). TC was found to have a positive and statistically significant moderating effect on the relationship between PW and CX at the Mean ($\beta = 0.470$, $p < 0.001$) and -1 SD ($\beta = 0.417$, $p = 0.001$) levels. However, no statistically significant moderating effect was found at the +1 SD level (H_8 partially supported).

The results of the moderator variable's moderating effect on indirect effects help develop a more complex and deeper understanding. According to the analysis results, positive, statistically significant indirect effects were observed for TC at all levels (+1 SD, Mean, -1 SD). In (+1 SD: $\beta = 0.110$, $p = 0.009$; Mean: $\beta = 0.099$, $p = 0.002$; -1 SD: $\beta = 0.088$, $p = 0.013$), Us (+1 SD: $\beta = 0.172$, $p = 0.016$; Mean: $\beta = 0.155$, $p = 0.007$; -1 SD: $\beta = 0.137$, $p = 0.027$) and VA (+1 SD: $\beta = 0.111$, $p = 0.009$; Mean: $\beta = 0.100$, $p = 0.001$; -1 SD: $\beta = 0.089$, $p = 0.007$) variables have a positive indirect effect on CX through PC at all levels of TC ($H_{9(a),(c),(d)}$ Supported). Similarly, at all levels of the moderating variable, VA (+1 SD: $\beta = 0.118$, $p = 0.034$; Mean: $\beta = 0.150$, $p = 0.001$; -1 SD: $\beta = 0.181$, $p = 0.008$) variable has a positive and statistically significant

indirect effect on CX through PW ($H_{10(d)}$ Supported). However, in the $Us \rightarrow PW \rightarrow CX$ path, only the moderating effect of TC at the -1 SD level ($\beta = 0.098$, $p = 0.031$) was found to be statistically significant ($H_{10(c)}$ partly supported). The hypotheses in the other paths in Table 5 ($H_{9(b),(e)}$ $H_{10(a),(b),(e)}$) could not be supported.

Table 5. Hypotheses Testing: The Moderating Effect of TC.

Effect	Hypotheses	Path	TC at ...	β	t	p Values	Sig.
Direct	H ₇	PC $\rightarrow$ CX	+1 SD	0.523	3.461	0.001	Yes
			Mean	0.470	4.930	<0.001	Yes
			-1 SD	0.417	3.370	0.001	Yes
	H ₈	PW $\rightarrow$ CX	+1 SD	0.252	1.898	0.058	No
			Mean	0.320	3.637	<0.001	Yes
			-1 SD	0.387	3.260	0.001	Yes
Indirect	H _{9(a)}	In $\rightarrow$ PC $\rightarrow$ CX	+1 SD	0.110	2.615	0.009	Yes
			Mean	0.099	3.084	0.002	Yes
			-1 SD	0.088	2.489	0.013	Yes
	H _{9(b)}	SP $\rightarrow$ PC $\rightarrow$ CX	+1 SD	0.054	1.261	0.207	No
			Mean	0.048	1.240	0.215	No
			-1 SD	0.043	1.093	0.274	No
	H _{9(c)}	Us $\rightarrow$ PC $\rightarrow$ CX	+1 SD	0.172	2.405	0.016	Yes
			Mean	0.155	2.690	0.007	Yes
			-1 SD	0.137	2.217	0.027	Yes
	H _{9(d)}	VA $\rightarrow$ PC $\rightarrow$ CX	+1 SD	0.111	2.595	0.009	Yes
			Mean	0.100	3.229	0.001	Yes
			-1 SD	0.089	2.680	0.007	Yes
	H _{9(e)}	OD $\rightarrow$ PC $\rightarrow$ CX	+1 SD	0.050	1.008	0.313	No
			Mean	0.045	1.008	0.313	No
			-1 SD	0.040	0.912	0.362	No
	H _{10(a)}	In $\rightarrow$ PW $\rightarrow$ CX	+1 SD	0.021	0.952	0.341	No
			Mean	0.026	1.236	0.216	No
			-1 SD	0.032	1.288	0.198	No
	H _{10(b)}	SP $\rightarrow$ PW $\rightarrow$ CX	+1 SD	0.028	0.959	0.338	No
			Mean	0.035	1.207	0.227	No
			-1 SD	0.043	1.225	0.221	No
	H _{10(c)}	Us $\rightarrow$ PW $\rightarrow$ CX	+1 SD	0.064	1.169	0.243	No
			Mean	0.081	1.865	0.062	No
			-1 SD	0.098	2.156	0.031	Yes
	H _{10(d)}	VA $\rightarrow$ PW $\rightarrow$ CX	+1 SD	0.118	2.117	0.034	Yes
			Mean	0.150	3.315	0.001	Yes
			-1 SD	0.181	2.647	0.008	Yes
	H _{10(e)}	OD $\rightarrow$ PW $\rightarrow$ CX	+1 SD	-0.002	0.089	0.929	No
			Mean	-0.003	0.104	0.917	No
			-1 SD	-0.004	0.110	0.912	No

5.4. Discussion of Study 2

Study 2 was conducted to gain a deeper understanding of TC's moderating role in these relationships. A distinctive feature of this study is that participants received comprehensive training and practice in using an AI-powered financial assistant prior to the main experiment. This methodological measure ensured that participants had the essential skills to interact with the chatbot, thereby enabling a more precise analysis of how different levels of TC influence the complex relationships among financial assistant features, user perceptions (PC, PW), and CX.

The initial analyses of Study 2 (values in parentheses in Table 3) (without moderator effects) revealed the basic direct and indirect effects of financial assistant features on user perceptions and CX. In terms of direct effects, the financial assistant's In, Us, and VA variables had positive, significant effects on PC. Similarly, the variables Us and VA were found to have positive and significant effects on PW. Furthermore, both PC and PW variables were found to have a positive, significant effect on CX. These findings demonstrate that the similar basic relationships observed in Study 1 were also consistently observed in this study. However, in Study 2, when analyses were conducted without accounting for the moderating effect of TC, none of the indirect effects of the Stimulus variables (In, SP, Us, VA, OD) on CX through PC and PW were statistically significant.

The most important contribution of Study 2 is that it reveals TC's moderating role in the relationships among financial assistant features, user perceptions, and CX. The findings detail how TC affects the strength and direction of these relationships. A statistically significant positive moderating effect of TC on the relationship between PC and CX was calculated. This suggests that as TC increases, the positive effect of PC on CX becomes stronger, thereby underscoring the crucial role of competence in complex financial tasks.

As TC increases, the positive effect of PW on CX was significant at the mean and -1 SD levels, but not at the $+1$ SD level. This suggests that PW has no effect on CX or is of secondary importance in situations with high financial TC. The positive moderator effect of TC at all levels in the paths where indirect effects exist, namely $In \rightarrow PC \rightarrow CX$, $Us \rightarrow PC \rightarrow CX$, $VA \rightarrow PC \rightarrow CX$, and $VA \rightarrow PW \rightarrow CX$, indicates that CX in complex financial tasks increases more than the existing effect. A similar situation is observed in the low level (-1 SD) TC moderation in the $Us \rightarrow PW \rightarrow CX$ pathway. The absence of a significant moderating effect of TC on some indirect effects in the Stimulus phase suggests that TC does not alter the mediating mechanism or that its effect operates through different channels.

In general, the findings of Study 2 indicate that the effects of financial assistant features on user perceptions and CX are complexly intertwined with contextual factors such as TC. Specifically, interactions based on PC remained strong regardless of TC, while some interactions based on PW may weaken at high complexity levels. It is believed that the financial assistant training provided for participants enabled them to observe these interactions more clearly, as users were able to express their perceptions and experiences more distinctly when basic competencies were provided. These results emphasize the importance of considering TC levels in financial assistant design and development strategies to optimize user experience, as well as the critical importance of competence perception in all types of financial tasks.

6. General Discussion

6.1. Overview and Summary

The two studies conducted in this research present essential findings on how AI-powered financial assistant features (Arousal) that Gen Z users interact with through mobile banking applications shape their internal perceptions (Organism) and ultimately affect their CX (Response). The results of Study 1 reveal that the social and aesthetic dimensions of the financial assistant shape the experience through user perceptions. Specifically, the financial assistant's SP and OD positively affect users' PC level, while VA has a significant effect on PW. These two fundamental perceptions, competence and warmth, ultimately increase CX in a positive and meaningful way. Furthermore, indirect effect analyses have shown that the social dimension of the financial assistant is closely tied to the perception of competence. In contrast, the aesthetic dimension is closely intertwined with the perception of warmth, ultimately shaping the overall experience. However, the fact that factors such

as In and Us did not show a significant effect in this model highlights the importance of Study 2, suggesting that these relationships may emerge under different conditions.

Study 2 validated these findings with a group of participants who had received prior training in the use of financial assistants and examined the moderating role of the TC variable, thereby providing a deeper understanding of the relationships. In this study, it was observed that even before considering TC, characteristics such as Interaction and Us already had significant effects on PC. However, the most critical finding is the central role of TC in these relationships. As TC increases, the positive effect of PC on CX becomes stronger; conversely, the effect of PW becomes statistically insignificant at high levels of complexity. This suggests that users value a financial assistant's ability to perform tasks correctly over their perceived friendliness in challenging financial situations. Furthermore, the moderating effect of v has revealed many indirect effects (e.g., $Us \rightarrow PC \rightarrow CX$) that were not observed in Study 1 or were insignificant in the basic model of Study 2, thereby clearly elucidating the underlying mechanisms.

The effects observed in Study 1 can be explained by the S-O-R framework, which serves as the theoretical basis for the research. Within this framework, the relationship between the Stimulus (S) and the Organism (O) is grounded in the Heuristic-Systematic Model (HSM). Users form quick initial judgments about the financial assistant's competence and warmth by using superficial and heuristic cues such as the assistant's visual design or SP. The relationship between Organism (O) and Response (R) is explained by the Expectation-Confirmation Model (ECM). These heuristically formed perceptions of competence and warmth create expectations, and the final CX is shaped by the extent to which these expectations are met (validated) after interaction with the financial assistant.

However, Study 2's findings present a more complex picture by showing how these theoretical interactions differ in the context of TC. When TC is low, users are expected to rely on heuristic processing and experience a sensory-based experience based on cues such as warmth. However, as TC increases, users are compelled to move beyond purely heuristic cues and adopt a more systematic, analytical, and in-depth processing approach. In this case, PC, which represents the financial assistant's actual problem-solving ability, becomes of primary importance to the CX. At the same time, the effect of more superficial and sensory factors, such as warmth, decreases. Therefore, TC emerges as a critical contextual factor that shapes the likelihood of users relying on heuristic versus systematic processing pathways, thereby influencing whether perceptions of warmth or competence become more salient in the final experience.

6.2. Theoretical Implications

This study aims to explain the experience of Generation Z consumers with AI-powered chatbots by drawing on three fundamental theoretical frameworks: the S-O-R model [37,38], the Heuristic-Systematic Model (HSM) [29], and the Expectancy-Confirmation Model (ECM) [32,33], thereby offering a multi-layered and significant theoretical contribution to the literature. Through this integration, the study explains the psychological processes that shape users' perceptions of chatbot features and ultimately shape the formation of the CX from a holistic perspective.

First, this study successfully applies the S-O-R framework to AI-powered fintech chatbots and the rapidly evolving context of digital natives, such as Generation Z [111], thereby reinforcing the theory's validity and applicability. It is well known that recent studies on artificial intelligence in finance frequently use the S-O-R framework [2,43,49,112]. This study has operationalized the abstract components of the S-O-R model, which is accepted as a well-reasoned theoretical framework [49,113] in financial technology contexts, with concrete variables. In this context, the social features, Us, and design dimensions

of the fintech chatbot—often highlighted as critical retention factors [70,114]—have been conceptualized as the environmental (S)timulus. The (O)rganism, which represents the user’s internal cognitive and emotional states, is represented by PC and PW [53]. These are the fundamental determinants of humanness in social psychology and are used as mediating variables in fintech adoption studies [20,54], a view strongly supported by recent findings on the ‘AI Banker’ persona [69,115]. Finally, the (R)esponse to these stimuli and internal states is considered as CX, consistent with the growing focus on experience in digital banking [17,89]. This structure confirms the S-O-R model’s strength as a framework for explaining fintech–human interactions [83].

As a second and more original theoretical contribution, this study successfully integrates HSM and ECM to explain the internal mechanisms of the S-O-R framework within the fintech landscape. This integration fills an essential gap in the literature by adding psychological depth to the Stimulus–Organism (S → O) relationship through the HSM [29]. With this approach, characteristics such as the design and interaction style of the fintech chatbot [114,116] have been conceptualized as heuristic cues that enable users to quickly form judgments about the financial AI’s potential competence and warmth without engaging in deeper analysis. In the model’s continuation, the relationship between Organism and Response (O → R) is explained as a dynamic process through the ECM [32,33,113]. The initial competence and warmth perceptions created through HSM represent users’ initial expectations of the financial service [34,35], and the final CX is shaped by the extent to which these expectations are met after actual use [89,117]. The integration of these two models under the S-O-R framework provides a comprehensive theoretical roadmap spanning from first impressions to final evaluations [118].

Finally, this study makes a significant contribution to literature by moving beyond a static model and demonstrating how an important contextual factor, such as TC, alters these theoretical relationships. The literature has also identified a moderating role of TC in the relationship between fintech chatbot communication styles and user trust [85,95,98]. Even a study using the S-O-R framework has included the moderating effect of TC [101]. The findings of this study provide a theoretical inference by revealing that TC has a critical effect on the functioning of HSM. When TC is low, users are likely to resort to heuristic processing, whereas as complexity increases, they are expected to shift to systematic processing, a more analytical form of thinking [29,40]. Indeed, our findings support this theoretical expectation by showing that, at high complexity, the perception of competence becomes critical for CX. At the same time, the effect of the PW decreases—a phenomenon recently corroborated in AI service quality studies [69,103]. This suggests that the relationships defined by S-O-R, HSM, and ECM are not universal but may vary in strength depending on contextual factors such as the nature of the financial task [119].

6.3. Practical Implications

The findings of this study offer valuable, actionable insights for managers, marketing professionals, and fintech developers who reach consumers through mobile apps, particularly for enhancing the experience of Generation Z customers. In today’s market, where customer expectations are rapidly changing with technological advancements [3] and financial institutions are prioritizing 24/7 online service delivery [2,120], the effectiveness of fintech chatbots is not only seen as a tool to reduce customer calls and workload [4,121,122] but also as an essential factor in enhancing CX [13,14,123].

First, our findings clearly confirm the importance of “first impressions” in financial services marketing and design, as emphasized by Araujo [21]. The author highlights how the introduction and framing of a fintech chatbot significantly affect consumer perceptions. The results of our study support this finding, showing that even for the highly digitally

fluent Generation Z [24,111], it is not only what a financial AI says but also how it looks and presents itself that is critical. In Study 1, VA was found to be a visual stimulus that creates appeal in consumers [15] and directly affects PW, OD, and PC—a relationship consistent with recent evidence linking perceived humanness to adoption intentions in banking [115]. SP was found to influence PC. This situation provides the following practical advice to fintech managers: a significant portion of digital investment should be allocated to visual interface design that evokes a sense of trust and sincerity in the user [114], creating a human-like identity (name, avatar) [21] and social cues that give the user the feeling that there is someone on the other side [70]. For example, a fintech chatbot designed for balance inquiries or transaction history checks may benefit from a visually warm interface featuring a human-like avatar, a friendly name, and socially present greetings (e.g., “Hi, I’m your digital assistant, how can I help you today?”). Consistent with our Study 1 findings, such design cues enhance perceived warmth and competence, thereby strengthening the overall customer experience.

Second, the findings show that the fintech chatbot’s basic functionality and ease of use become critical as users interact more with the financial service [113,124]. For instance, during routine but multi-step actions such as setting payment reminders, scheduling bill payments, or transferring funds, the chatbot should minimize interaction steps, provide clear confirmations, and deliver immediate feedback. Consistent with our Study 2 findings, usability and interaction quality in these scenarios enhance perceived competence, particularly as users gain experience with the financial assistant. In Study 2, factors such as Us and interaction quality were found to have a significant effect on the PC of the chatbots. If the initial attractive design is not supported by seamless Us and a smooth interaction that enhances user adoption [21,119], which are critical for the long-term digital CX in finance [17,57,58], the AI advisor will be perceived as inadequate and negatively affect the CX [125]. Therefore, continuously improving the interface based on user feedback and ensuring a seamless flow of financial interaction are essential for long-term success [117,123].

The final and most important practical implication is that strategy differentiation based on TC is an absolute necessity [40]. The literature also suggests that TC is a significant factor influencing consumer attitudes [95] and regulating trust in fintech chatbots [101]. In particular, it is known that while users prefer chatbots for simple information exchanges, the conversational style weakens trust perception in complex tasks, and a goal-oriented communication style is more widely adopted [98,119]. Our study takes this finding a step further by revealing how TC changes the human-like characteristics that a financial AI should possess. Complex financial tasks may require consumers to expend additional cognitive resources to reach a decision [93]; therefore, chatbots designed for such tasks should employ a distinct communication style. In fintech chatbots, which are designed for simple and routine tasks, factors that directly affect CX [20] and foster strong relationships [53] can be prioritized. In contrast, for complex tasks such as resolving technical issues or fraud alerts [85], the AI advisor’s primary focus should be competence, which consumers more positively perceive [79] and demonstrates the service’s ability to adapt to changing conditions [53]. Our study demonstrates that in such situations, the perception of warmth loses its importance, and a chatty or overly friendly bot may even cause users more stress and be perceived as inadequate—a conclusion supported by recent evidence showing that ‘fun’ elements do not necessarily enhance service quality in utility-focused interactions [69]. For example, a conversational chatbot tone may suit low-complexity tasks such as balance checks or ATM location, but our findings suggest it can be counterproductive in high-complexity contexts. In situations involving fraud alerts, account freezes, or failed transactions, users prefer concise, purposeful communication focused on accuracy and

resolution speed. Accordingly, chatbots handling complex financial tasks should prioritize competence cues over warmth-oriented features.

Additionally, when financial AI reaches the limits of its problem-solving capabilities, it is critical to design mechanisms that seamlessly and quickly transfer the user to a human representative. As noted in the literature, as TC increases, the perceived problem-solving ability of artificial intelligence decreases [96], and users are already aware of the limitations of automated agents in handling complex queries [26,40]. Accordingly, fintech firms should adopt a task-adaptive chatbot design strategy rather than relying on a one-size-fits-all conversational approach. However, while designing these experiences, it is crucial to address the 'dark side' of AI-powered interactions. Beyond enhancing efficiency, fintech developers must mitigate risks such as algorithmic bias, which can lead to misinformation in financial advice, and data privacy concerns that frequently cause anxiety among Generation Z users. In high-complexity financial tasks, a chatbot's failure to provide accurate information or to implement a transparent security protocol can turn a positive customer experience into a significant threat perception, potentially leading to trust erosion and brand abandonment. Therefore, the purposeful communication style emphasized in this study should also incorporate robust risk disclosure and seamless escalation to human agents to manage potential AI failures. Furthermore, managers must recognize that for Generation Z, being tech-savvy does not imply a lack of skepticism. Trust serves as a fundamental mediator between a chatbot's perceived competence and the user's ultimate satisfaction. To appeal to this generation of conscious consumers, fintech providers should prioritize not only the originality of design but also the demonstrability of security and reliability. Building trust through transparent communication protocols is essential for fostering long-term engagement with AI-driven financial services.

In summary, financial institutions can strategically design and position fintech chatbots based on users' experience levels and the nature of the financial task they intend to perform [40,111], thereby transforming this technology from a mere cost center into a strategic driver of loyalty and satisfaction for Generation Z [17,123].

7. Limitations

This study provides valuable theoretical and practical insights into Generation Z's chatbot experiences; however, the results should be interpreted with certain limitations in mind. Both Study 1 and Study 2 employed convenience sampling among university-aged individuals in Türkiye, which limits the generalizability of the findings beyond this specific demographic and cultural context. These limitations also present valuable opportunities for future research.

First, due to economic and accessibility constraints, the sample for this study was selected using convenience sampling. This method may limit the sample's ability to represent the entire Generation Z population in Türkiye fully. Furthermore, the study is limited to Generation Z individuals residing in Türkiye. Considering the effect of cultural differences on perceptions of technology and communication expectations, the validity of the findings should be tested across diverse geographical and cultural contexts. Future studies employing probability-based sampling methods and cross-cultural comparative designs—potentially involving other cohorts, such as Generation X—could enhance the generalizability of these findings. Additionally, the high proportion of female participants in both Study 1 (71.7%) and Study 2 (65.6%) should be noted as a potential limitation. Existing literature indicates that gender can influence perceptions of AI anthropomorphism and social presence, with some studies suggesting that females may respond more strongly to perceived warmth. Although our structural model yielded significant results, this gender imbalance might have influenced the weight of the social and affective paths.

Future research should aim for a more gender-balanced sample to determine whether these relationships differ significantly between male and female users of fintech chatbots.

Second, the research design has a cross-sectional structure; that is, data were collected at a specific point in time. While this approach successfully reveals relationships and correlations among variables, it is limited in establishing causal relationships. For example, while this study demonstrates that chatbot features affect CX, it does not provide insight into how this experience evolves or how prolonged interaction with a chatbot alters perceptions. Future research could use longitudinal studies to deepen understanding of the evolution of user perceptions and continuance intention over time or employ experimental designs to test the effects of specific chatbot features more precisely.

Third, this study focused on a chatbot application for a service provider app on a smartphone. The nature of tasks in this sector and customer expectations may differ from those in other sectors, such as e-commerce, banking, or healthcare. For example, “warmth” and “sociability” may be more important in an e-commerce chatbot. At the same time ‘competence’ and “security” may be much more dominant in a banking chatbot—a distinction supported by recent findings that utilitarian value often supersedes entertainment in financial contexts. Therefore, studies that test the model’s validity across different industries will reveal the extent to which the findings are sensitive to the industry context.

Finally, although the research model used in this study is comprehensive, it does not include all potential variables that may influence Gen Z’s chatbot experience. Factors such as the user’s personality traits, previous relationship with the brand, or the content and emotional tone of the conversation with the chatbot may also shape the experience. Future studies could incorporate these and similar variables, such as perceived security and fraud risk sensitivity, into the model to develop a more comprehensive understanding of the interactions between Generation Z and AI. Furthermore, while this study predominantly focused on the positive drivers of customer experience, future research should explicitly examine the deterrent effects of perceived risks, such as financial fraud susceptibility, cybersecurity threats, and the psychological impact of AI-driven errors. Incorporating variables like ‘Perceived Risk’ or ‘Privacy Concern’ into the S-O-R framework would provide a more balanced and holistic understanding of the barriers that prevent Generation Z from fully embracing AI-powered fintech solutions.

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