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The Impact of Digital Assistants on Customer Satisfaction: A Study of Interactive Artificial Intelligence Applications in Turkey

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ABSTRACT

Digital assistants such as Siri and Google Assistant have become ubiquitous companions in modern life, supporting users in tasks ranging from information retrieval to daily decision-making. Despite their widespread use, existing research has primarily emphasized technical performance, overlooking the interactive and psychological mechanisms that shape customer satisfaction. In particular, the interactive dimensions of human–AI communication—controllability, synchronicity, and bidirectionality—remain underexplored, limiting understanding of how real-time responsiveness and user control influence satisfaction. As digital assistants increasingly resemble social partners, user satisfaction is shaped not only by functional performance but also by perceptions of agency, trust, and cognitive comfort. To address this gap, this study draws on Expectation–Confirmation Theory and analyzes survey data from 453 users using the R statistical environment (version 4.5.1). The results demonstrate that controllability, synchronicity, and bidirectionality significantly enhance satisfaction. Moreover, perceived trust and self-efficacy strengthen the positive influence of expectation confirmation, while information privacy concerns do not significantly moderate this relationship. These findings highlight the psychological foundations of satisfaction in AI-mediated interactions and shift the focus from technical optimization to human-centered interaction design, providing practical insights for developers and marketers seeking to create transparent, trustworthy, and emotionally engaging digital assistants.

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1. Introduction

AI-powered digital assistants are designed to perform tasks or services based on user commands or queries (Balcıoğlu et al., 2022). The term "digital assistant" refers to a variety of technologies, including voice assistants, AI-enabled chatbots, and chatbot assistants. However, "Digital Assistant" is a broader category that encompasses all these technologies (Sharma et al., 2024). Popular examples such as Google Assistant, Alexa, Siri, and Cortana offer diverse capabilities, including setting reminders, retrieving information, and controlling home automation systems (Kraus et al., 2021). As reported by Statista (2022), the global use of digital voice assistants is expected to double, rising from 4.2 billion in 2020 to 8.4 billion by 2024. Additionally, chatbots are rapidly taking the place of human customer service representatives across various sectors and are projected to manage over 90% of online customer service interactions by 2025 (Maduku et al., 2023).

A defining feature of digital assistants is their ability to understand and process natural language, enabling users to interact with them in a conversational manner (Lindquist et al., 2008). This functionality is often enhanced by speech recognition and synthesis technologies, allowing digital assistants to interpret voice commands and provide spoken responses. Consequently, they are particularly useful in hands-free situations such as driving or cooking. Additionally, many digital assistants offer personalized recommendations based on users' preferences and behaviors, learning from past interactions to improve their performance over time (Bayus et al., 1997). These developments in artificial intelligence (AI) have greatly streamlined and simplified many aspects of daily life, highlighting the increasing significance and utility of digital assistants in modern society. Given the substantial investment businesses have made in digital assistant technology and customer service procedures, it is vital to assess how well user expectations match the technology's actual performance.

Previous studies emphasize the importance of customer engagement in boosting satisfaction and enhancing productivity (Yim et al., 2012). Factors related to self-efficacy—such as self-confidence, beliefs, skill acquisition, and pride—play a crucial role in how users evaluate their proficiency with digital assistants (Brill et al., 2022). These beliefs are likely to impact user satisfaction. To understand this relationship, we use Social Cognitive Theory (SCT), which examines the interplay between personal factors, behaviour, and the environment. SCT emphasizes that self-efficacy, shaped by observational learning and self-regulation, affects how users engage with technology and their overall satisfaction (Bandura, 1986). Our research explores how users' confidence in their abilities influences their satisfaction with digital assistants and AI-related technologies.

Recent advancements in machine learning have enabled the discovery of hidden patterns and personal insights from data, significantly enhancing user personalization (Cartwright, 2005). Businesses can use mobile devices to detect consumer locations and tailor their offerings accordingly (Küpper, 2005; Varshney & Vetter, 2002). However, this increased data capability also raises concerns about the potential misuse or abuse of digital data (Miltgen et al., 2013). As users become more concerned about protecting their personal data (De Cosmo et al., 2021), it becomes essential to understand how these privacy concerns and perceptions of trust impact the use of digital assistants. If businesses fail to protect user data, they risk losing consumer trust and jeopardizing their reputation (Pappas, 2016). To explore these dynamics, we apply Protection Motivation Theory (PMT), which explains how individuals respond to threats to their personal information (Maddux & Rogers, 1983). By applying PMT, we examine how privacy concerns and trust perceptions influence user interactions with digital assistants, helping businesses strike a balance between the benefits of personalization and the necessity of maintaining user trust.

Digital assistants engage users in real-time, facilitating bidirectional communication between the user and the computer (Coyle & Thorson, 2001). In the realm of digital services, interactivity includes controllability, synchronicity, and bidirectionality (Fortin & Dholakia, 2005; Yoo et al., 2010). Despite producers' efforts to enhance digital assistant applications for greater interactivity and improved performance—aimed at increasing user satisfaction—empirical literature has given little attention to these initiatives (Purwanto et al., 2020). In this study, we examine how these dimensions of interactivity impact perceived performance and affect consumer satisfaction with artificial intelligence applications.

The marketing literature has long emphasized the significance of customer satisfaction (Rego et al., 2013). However, research specifically focusing on customer satisfaction with AI-powered digital assistants—particularly concerning interactive features such as controllability, synchronicity, and bidirectionality—remains limited. This gap in research presents an opportunity to provide valuable insights for companies developing AI-driven digital assistants. While previous studies have examined the overall impact of digital assistants on satisfaction, they have primarily focused on broader factors such as expectation confirmation and usability (Abdelmoneim et al., 2024; Brill et al., 2022; Kiseleva et al., 2016; Sohail, 2020). Research has also explored AI assistants in various contexts, including workplace efficiency and employee satisfaction (Dutta & Mishra, 2021; Ossadnik et al., 2023), as well as AI adoption in education, where digital assistants provide support services but face usability limitations (Öncü & Süral, 2024). Additionally, concerns surrounding AI trust, privacy, and transparency have been examined as key factors influencing user engagement and satisfaction (Jang, 2020). Despite these contributions, the specific impact of interactivity features on customer satisfaction remains underexplored. While some studies have investigated AI assistants' ability to maintain conversational context (Kiseleva et al., 2016) and facilitate voice-based interactions (Jang, 2020), the effects of controllability, synchronicity, and bidirectionality on user satisfaction remain unclear. To address this gap, this study adopts Expectation Confirmation Theory (ECT) and integrates cognitive factors such as self-efficacy, privacy concerns, and trust to provide a more comprehensive understanding of customer satisfaction. This research also aims to offer practical insights for AI developers, emphasizing the importance of responsiveness and user control. To explore these relationships, this study will examine the following questions:

RQ1: How does Expectation Confirmation Theory explain customer satisfaction with digital assistants?
RQ2: What is the impact of digital assistants' interactivity features—controllability, synchronicity, and bidirectionality—on perceived performance and user satisfaction?
RQ3: How do cognitive factors, such as self-efficacy, information privacy concerns, and perceived trust, moderate these relationships?

This research makes three significant contributions to the marketing literature and management. First, it enhances our theoretical grasp of customer satisfaction within the context of interactive artificial intelligence applications. Second, it extends the theoretical framework by integrating socio-cognitive theories—namely, Expectation Confirmation Theory (ECT), Social Cognitive Theory (SCT), and Protection Motivation Theory (PMT)—with cognitive factors such as self-efficacy, information privacy concerns, and perceived trust to provide a more comprehensive explanation of customer satisfaction with digital assistants. Lastly, by identifying key dimensions of interactivity that should be prioritized, this study offers practical insights that can guide marketing managers and practitioners in designing digital assistants that better meet consumer needs and expectations. Additionally, by examining a sample from Turkey, a developing country that has not been extensively studied, this research enriches the literature on satisfaction with digital assistants from a less explored context.

The remainder of this study is organized as follows: In the subsequent section, we review the theoretical background and outline our study's hypotheses. The third section presents our research methodology and the corresponding results. Finally, we discuss the study's limitations and offer recommendations for future research.

2. Literature Review

2-1. Expectation Confirmation Theory

Expectation confirmation theory is a fundamental theoretical framework that explains how customer expectations contribute to the development of satisfaction (Brown et al., 2012). According to ECT, customers form expectations regarding a product or service based on their previous experiences, information from others, and marketing communications. Satisfaction arises when a product or service meets or exceeds these expectations; conversely, if actual performance falls short, customers experience disconfirmation and dissatisfaction (Oliver, 1980). The ECT model indicates that satisfaction is determined by two primary processes: setting expectations and subsequently confirming or disconfirming them. Approval or disapproval stems from evaluating perceived performance via a comparison process (Oliver et al., 1994).

2-2. Customer Satisfaction

Customer satisfaction is a response that reflects a consumer's sense of fulfillment (Oliver & Burke, 1999). It involves assessing whether a product or a service has achieved or is providing an adequate level of fulfillment associated with the consumption experience. This assessment includes scenarios where the level of fulfillment meets expectations, as well as those where it exceeds or falls short of them (Schiebler et al., 2025).

2-3. Expectations

Beliefs and assumptions that customers hold before experiencing a product or service constitute their expectations (Oliver, 1980). Expectations have been defined as the fundamental driving force behind customer satisfaction (Oliver, 1980; Zeithaml et al., 1993). When a customer's expectations are not met, they are likely to experience dissatisfaction with the service or product. In contrast, if the service or product fulfils or exceeds their expectations, they are more likely to feel satisfied (Brill et al., 2022).

2-4. Perceived Performance

Performance can be assessed in two distinct ways: objective performance and perceived performance (Brill et al., 2022). Objective performance refers to the actual, tangible effectiveness of a product or service, whereas perceived performance involves a subjective evaluation by the user. Perceived performance is about a person’s mental assessments of a product’s features, their levels, or the outcomes associated with them (Spreng & Olshavsky, 1993). In this study, we focus on perceived performance because detailed factual performance data for digital assistants are not easily accessible to many people.

2-5. Confirmation of Expectations

Like many other research endeavors, this study faces the challenge of the lack of a universally accepted definition or measurement for "confirmation” (Brill et al., 2022). Nonetheless, it is widely agreed that confirmation involves a cognitive comparison between expected outcomes and actual performance (Oliver, 1981). Objective confirmation and subjective confirmation are two categories into which confirmation can be classified. Objective confirmation, as defined by Olshavsky and Miller (1972), is the difference between expected outcomes and actual performance. On the other hand, subjective confirmation, as described by Brill et al. (2022), is the gap between expectations and perceived performance. In our research, we rely on perceived measures rather than objective ones, as most users lack access to the actual performance results of digital assistants.

2-6. Perceived Trust

Perceived Trust relates to a person’s assessment of the reliability and integrity of technology (Abdelmoneim et al., 2024). It empowers individuals with the confidence to navigate uncertainties and risks, facilitating trust-based interactions with internet-connected devices (McKnight et al., 2002). Higher perceived trust levels are associated with reduced perceived risks related to information quality and reliability, significantly enhancing users' interactions with AI-based digital assistants (Purwanto et al., 2020). Users who trust service providers, such as Google, Amazon, and Apple, to uphold privacy standards are more likely to adopt and continue using their devices. Conversely, non-users who have higher privacy concerns and lower confidence in data security are significantly less inclined to consider adopting intelligent personal assistants (IPAs). This highlights trust as a crucial factor in technology acceptance (Liao et al., 2019). In this study, we adopt a definition of perceived trust that reflects customers’ subjective trust beliefs formed during the trust-building process. We focus on customers’ perceptions of a specific vendor or product’s attributes, including competence, benevolence, and integrity (Brill et al., 2022; Komiak & Benbasat, 2006). Competence refers to the perceived ability of the digital assistant to perform its functions effectively; benevolence captures the extent to which the provider is believed to act in the user’s best interest, and integrity reflects the belief that the provider adheres to acceptable principles and ethical standards (Venkatesh et al., 2011).

2-7. Information Privacy Concerns

The quick adoption of digital assistants in daily life has raised considerable worries about the privacy and security of personal information (Liu & Malkin, 2022; McLean & Osei-Frimpong, 2019). Users struggle to balance technological advancements with potential privacy risks (Ebbers et al., 2021). Digital assistants are often perceived as intrusive, constantly monitoring and collecting sensitive information, which heightens anxiety over data privacy (Lutz & Newlands, 2021; Vimalkumar et al., 2021). In this study, we adopt a definition of information privacy concern that reflects users' apprehension about the potential misuse or unauthorized access of their personal data and their perceptions of how effectively digital assistants safeguard this information (Kim, 2008; Malhotra et al., 2004). Such concerns can discourage users from adopting such technologies despite their potential benefits (Acikgoz et al., 2023). As dependence on digital assistants grows, fears about private conversations being recorded and personal data being misused become more pronounced (Liao et al., 2020). Many users remain skeptical about the necessity of these technologies, questioning whether the benefits outweigh the risks (Keleher, 2023; Maier et al., 2023). At the same time, the "privacy paradox" complicates this issue—although users express strong privacy concerns, they often continue engaging with digital assistants (L. Chen et al., 2021). While they recognize the benefits digital assistants offer, they also worry about data misuse or unauthorized access to personal information. Striking a balance between the perceived utility of digital assistants and the risks associated with data privacy is crucial for ensuring sustained user engagement**.**

2-8. Self-efficacy

Self-efficacy pertains to an individual's confidence in their ability to effectively accomplish a particular task (Hou et al., 2023). This sense of confidence plays a crucial role in shaping how individuals perceive and intend to adopt AI-based technology services. When individuals believe they can effectively use AI technology, they are more likely to embrace and integrate these services into their daily lives (Chintalapati & Pandey, 2022). Research consistently shows that high self-efficacy positively influences the adoption and usage of AI-based digital assistants. For instance, Abiola and Ikegune (2016) demonstrate that students with higher computer self-efficacy feel more confident using personal digital assistants (PDAs) for academic activities. Furthermore, Ashrafi and Easmin (2023) highlight that technology self-efficacy (TSE) moderates the relationship between trust and the intention to use voice assistant services. In this study, we adopt a definition of self-efficacy that reflects users' confidence in their ability to effectively operate and interact with digital assistants (Compeau & Higgins, 1995). This construct captures three key aspects: magnitude, which concerns the perceived difficulty of tasks users believe they can accomplish; strength, which reflects the degree of confidence in successfully performing these tasks; and generalizability, which denotes the extent to which efficacy beliefs apply across different situations or contexts.

2-9. Controllability of Digital Assistants

Controllability refers to the degree to which users can direct or influence the actions and responses of a digital assistant. This capability ensures that the assistant functions effectively and meets user needs, ultimately leading to greater satisfaction. Perceptions of functional utility and dynamic control over the system are key factors influencing user satisfaction with AI assistants. Users specifically expect these assistants to perform tasks efficiently in response to their commands (Shao & Kwon, 2021). Moreover, controllability enables users to manage both the content and timing of their interactions with digital assistants (Purwanto et al., 2020).

2-10. Synchronicity of Digital Assistants

In the context of digital assistants, synchronicity refers to their ability to enable real-time interactions, allowing users to engage with them as if in a live conversation. This characteristic is crucial for delivering immediate feedback, which significantly enhances user experience and satisfaction. Research indicates that synchronicity in digital interactions fosters a greater shared understanding among users, which is a key factor in overall satisfaction with digital platforms, including digital assistants (Fleischmann et al., 2019; Golden & Fleischmann, 2018). Higher interactivity through synchronized communication improves the perceived performance of digital assistants like Siri and Alexa, fostering greater trust and loyalty among users (Purwanto et al., 2020).

2-11. Bidirectionality of Digital Assistants

Bidirectionality refers to the two-way flow of information facilitated by digital assistants (Baier et al., 2018). Purwanto et al. (2020) identified bidirectionality as an essential dimension of interactivity that contributes to digital assistant performance alongside controllability and synchronicity. It plays a significant role in shaping user trust and satisfaction, particularly concerning privacy and data security (Purwanto et al., 2020). The ability to communicate seamlessly in both directions enhances user confidence, ultimately contributing to a more satisfying interaction with the assistant.

Proposed Research Model

Based on expectation confirmation theory, we propose a research model (see Figure 1). The constructs of this model include perceived performance, expectations, confirmation of expectations, customer satisfaction, information privacy concerns, and perceived trust, as outlined by Brill et al. (2022). Additionally, we include the variable of self-efficacy. We also incorporated interactivity features of digital assistants—controllability, synchronicity, and bidirectionality—into the expectation-confirmation theory framework, as suggested by Purwanto et al. (2020).

Hypotheses Development

According to ECT, customer expectations regarding digital assistants play a key role in shaping satisfaction through the expectation assimilation effect (Brill et al., 2022). This effect suggests that when the gap between expectations and actual performance is small, individuals tend to adjust their perceptions and report higher satisfaction (Lankton & McKnight, 2012). In other words, satisfaction largely depends on the degree to which expectations are met (Jiang & Klein, 2009). The assimilation effect highlights a greater dependence on expectations over disconfirmation in shaping satisfaction (Lankton & McKnight, 2012). Based on this reasoning, we propose:

> **H1.** There is a positive relationship between expectations of digital assistants and customer satisfaction.

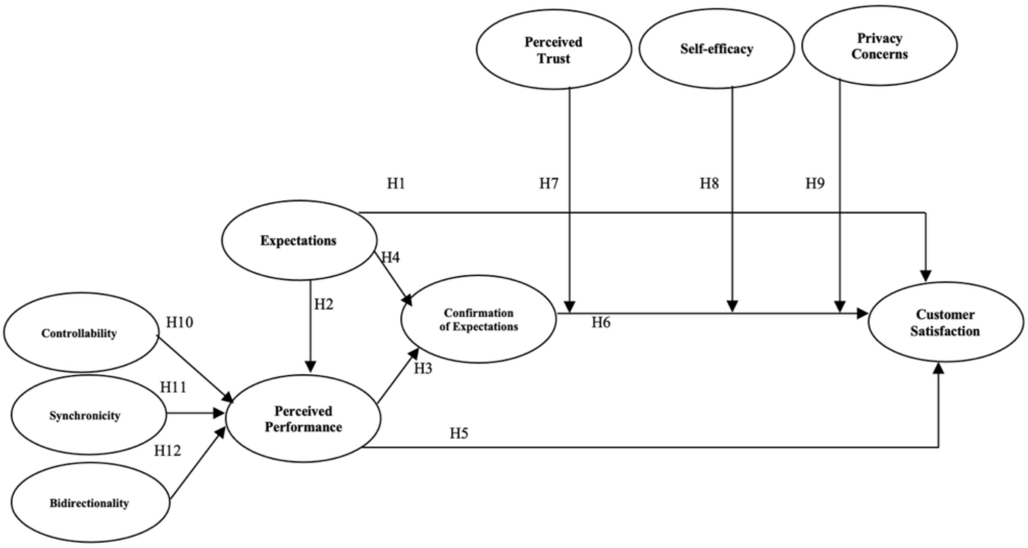

Fig. 1. Proposed Research Model

ECT suggests that consumers' perceptions of performance are influenced by the degree to which their expectations align with their actual experiences (Oliver, 1977). In this model, expectations act as a benchmark for evaluating performance (Lankton et al., 2014). Deakins and Dillon (2006) emphasize that aligning expectations with actual outcomes fosters constructive interactions between users and service providers. This is particularly relevant for digital assistants: when users anticipate a certain level of interaction quality, their evaluations reflect the alignment between expectations and experiences, which in turn affects their perception of the system's effectiveness. Accordingly, we propose:

> **H2.** There is a positive relationship between expectations of digital assistants and the perceived performance of digital assistants.

Evaluating the alignment between an individual's initial expectations and the performance or results they experience is referred to as confirmation. This assessment is crucial for understanding and influencing individual satisfaction. According to expectation confirmation theory, when performance meets or exceeds expectations—known as positive confirmation—it enhances satisfaction. Conversely, unmet expectations lead to negative confirmation (Bhattacherjee, 2001). In the context of digital assistants, if users perceive these technologies as effective in improving their performance, they are more likely to adopt and continue using them (Marikyan et al., 2022). Given these points, we suggest:

> **H3.** There is a positive relationship between the perceived performance of digital assistants and the confirmation of expectations for digital assistants.

ECT asserts that expectations significantly impact confirmation judgments, often explained by the halo effect (Brill et al., 2022). The halo effect occurs when an initial impression heavily influences subsequent judgments about new information (Tetlock, 1983). Users with high expectations tend to perceive outcomes that not only meet but also exceed their initial anticipations. Conversely, users with lower expectations often perceive outcomes that align with or fall short of their expectations. This dynamic establishes a positive correlation between expectations and their confirmation (Brill et al., 2022). Regarding digital assistants, user expectations, influenced by the capabilities of digital assistants, can lead to the confirmation of those expectations, thereby enhancing user satisfaction and engagement (Vandelanotte et al., 2024). Given these points, we suggest:

> **H4.** There is a positive relationship between expectations of digital assistants and confirmation of expectations for digital assistants.

Numerous studies have shown a positive relationship between perceived performance and customer satisfaction (Anderson & Sullivan, 1993; Brill et al., 2022; Churchill Jr & Surprenant, 1982). In this context, perceived performance refers to how customers assess the quality of a product or service. This link is rooted in the concept of value percept disparity—when a product or service fulfils users' needs or desires, it leads to greater satisfaction with their overall experience. Rather than relying solely on a comparison between expectations and actual outcomes, this perspective emphasizes perceived performance as the primary standard for evaluating satisfaction. Applied to digital assistants, when users perceive these technologies as delivering valuable and efficient support, their satisfaction enhances (Brill et al., 2022). Given these insights, we propose the following hypothesis:

> **H5.** There is a positive relationship between the perceived performance of digital assistants and customer satisfaction.

The expectation confirmation model assesses satisfaction via two primary procedures: the establishment of expectations and their confirmation by evaluating performance through a comparative process (Y. Chen et al., 2010). According to this model, satisfaction arises when consumers evaluate a product or service based on how well it meets or deviates from their initial expectations. In this confirmation/disconfirmation process, consumers compare their perceptions of actual performance against pre-existing standards—such as expectations or normative benchmarks. Satisfaction occurs when performance aligns with expectations (confirmation), while any mismatch leads to disconfirmation and potential dissatisfaction. When customers' expectations regarding digital assistants—whether related to functionality, user experience, or service quality—are met or exceeded, it results in higher levels of satisfaction (Biswas et al., 2019; Eren, 2021). Based on these insights, we propose the following hypothesis:

> **H6.** There is a positive relationship between confirmation of expectations for digital assistants and customer satisfaction.

Trust is a delicate concept, as it relies on consumers' beliefs (Dawar & Pillutla, 2000). It holds substantial importance in influencing consumers' decisions to adopt AI technologies and services. Trust helps mitigate perceived risks and uncertainties, thereby enhancing the willingness to accept and adopt these technologies (AlHogail, 2018). Research shows that higher levels of trust are linked to greater satisfaction with digital assistants (Brill et al., 2019; Choudhury & Shamszare, 2024; Marikyan et al., 2022). Given these points, we suggest:

> **H7.** Perceived trust plays a positive moderating role in the relationship between the confirmation of expectations for digital assistants and customer satisfaction.

Self-efficacy, defined as confidence in one's ability to succeed in a specific task, is essential for both achievement and motivation (Mathews, 2005). This self-confidence, along with an individual's conviction, skill and knowledge acquisition, and sense of pride, influences how users perceive their proficiency with digital assistants. Consequently, it follows that these self-efficacy beliefs can significantly affect users' satisfaction with digital assistants (Brill et al., 2022). Given these points, we suggest:

> **H8.** Self-efficacy plays a positive moderating role in the relationship between the confirmation of expectations for digital assistants and customer satisfaction.

Customers' concerns about privacy arise from feeling vulnerable and having a limited sense of control regarding their personal data (Dinev & Hart, 2004). These privacy concerns can lead to negative reactions that affect customers' willingness to share information. As a result, this can diminish trust and satisfaction with various platforms (Al-Jabri et al., 2019). Privacy concerns significantly influence consumer evaluations of digital assistants. Users who perceive greater privacy risks are more likely to restrict their interactions with these technologies, which, in turn, diminishes their overall satisfaction (Kronemann et al., 2023). Given these points, we suggest:

> **H9.** Information privacy concerns play a negative moderating role in the relationship between the confirmation of expectations for digital assistants and customer satisfaction.

The performance of digital assistants significantly improves when users are granted greater controllability. This enhanced control not only boosts the effectiveness of the digital assistant but also elevates the quality, sensitivity, and overall value of the service, ultimately leading to increased customer satisfaction (Purwanto et al., 2020). When users feel empowered during their interactions, they are more likely to view the assistant as effective and reliable. This sense of trust fosters greater satisfaction and encourages users to integrate such technology into their daily routines (Purwanto et al., 2020). Given these points, we suggest:

> **H10.** There is a positive relationship between the controllability of digital assistants and the perceived performance of digital assistants.

Digital assistants with synchronicity capabilities can instantly access relevant data and resources, enabling real-time responsiveness. This efficiency enhances reliability, comfort, and accuracy, meeting customer demands seamlessly. Higher levels of synchronicity improve user engagement, shaping perceptions of the assistant's performance. The immediacy of synchronous interactions fosters a more engaging experience, strengthening users' confidence in the assistant's capabilities (Purwanto et al., 2020). Given these points, we suggest:

> **H11.** There is a positive relationship between the synchronicity of digital assistants and the perceived performance of digital assistants.

The interaction between digital assistants and users is inherently bidirectional. While digital assistants provide services based on the information and resources they receive from customers, users also play a vital role in facilitating this exchange of data and information (Purwanto et al., 2020). Effective communication with digital assistants can significantly enhance user performance. By streamlining interactions, these assistants help reduce mental workload, allowing users to focus more on their primary tasks (Blocker et al., 2023). Based on these observations, we propose:

H12. There is a positive relationship between the bidirectionality of digital assistants and the perceived performance of digital assistants.

3. Methodology

3-1. Data Collection and Sample

We collected data from digital assistant users residing in Istanbul, Izmir, and Ankara—three major cities in Turkey—through an online survey conducted over a one-month period from August 2022 to September 2022. The online questionnaire was distributed via social media platforms (Facebook, WhatsApp, and Instagram). We chose these platforms because digital assistants operate in an internet-based environment, which suggests that users are familiar with online interactions. Our target respondents were adults aged 18 and older who use digital assistants. To ensure the relevance of responses, we included qualifying questions, allowing participants to proceed with the survey only after confirming their use of digital assistants.

We also clarified to participants that there were no right or wrong answers. All participants voluntarily completed the survey without any financial incentives. A total of 453 individuals took part in the study. Table 1 presents the demographic information of the respondents, revealing that approximately 60.3% identified as female, while 39.7% identified as male. Among the respondents, 45.3% were aged between 30-39 years, and 31.6% held a bachelor's degree. All participants (100.0%) reported using digital assistants, with the most common usage frequency categorized as “rare” at 26.3%. Additionally, among those who use digital assistants, 40.4% had been utilizing this technology for the past 2-3 years.

3-2. Measures

We measured all constructs using well-established scales from prior literature to ensure reliability and validity. Customer satisfaction was assessed using four items adapted from Brill et al. (2022) on a seven-point semantic differential scale. The first item ranged from extremely displeased to extremely pleased, the second from extremely frustrated to extremely contented, the third from extremely miserable to extremely delighted, and the fourth from extremely dissatisfied to extremely satisfied. We measured all other constructs on 7-point Likert scales ranging from 1 (strongly disagree) to 7 (strongly agree). We adapted perceived performance (3 items), confirmation of expectations (3 items), and expectations (3 items) from Lin et al. (2017). To assess the moderating roles of perceived trust (10 items), information privacy concern (8 items), and self-efficacy (14 items), we utilized scales developed by previous research (Askar & Umay, 2001; Kehr et al. 2015; Komiak & Benbasat, 2006). Lastly, we measured the interactivity features of digital assistants using the scale established by Purwanto et al. (2020). A pilot study was conducted with 30 respondents from the target population and nine academic experts tassess clarity and relevance. Based on their feedback, we made minor adjustments while preserving the integrity of the original measurements.

3-3. Analytical Methods

All statistical analyses were performed using R (Version 4.5.1; R Core Team, 2025). Confirmatory Factor Analysis (CFA), Structural Equation Modeling (SEM), and moderation tests analyses were performed with the “lavaan” package (Rosseel, 2012). Psychometric evaluations, including Composite Reliability (CR), Average Variance Extracted (AVE), and Heterotrait–Monotrait ratio (HTMT), were conducted with the "semTools" package (Jorgensen et al., 2012) and “psych” package (Revelle & Revelle, 2015). Reliability and descriptive statistics were computed using the “psych” package (Revelle & Revelle, 2015).

The CFA model was estimated using Maximum-Likelihood (ML) with robust standard errors and a mean structure. The latent factors were defined as follows: Customer Satisfaction (CS), Expectations (EXP), Perceived Performance (PP), Confirmation of Expectations (CE), Perceived Trust (PT), Information Privacy Concerns (IPC), Self-efficacy (SE), Controllability (CO), Synchronicity (SY), and Bidirectionality (BD). Model fit was evaluated using CFI ($\geq .90$), TLI ($\geq .90$), RMSEA ($\leq .08$) and SRMR ($\leq .08$), following Hu and Bentler (1999).

Table 1. Distribution of Participant Demographic Information and Digital Assistant Usage

Variable		Frequency	Percentage
Gender	Female	273	60.3
	Male	180	39.7
	Total	453	100.0
Age	18-29	97	21.4
	30-39	205	45.3
	40-49	91	20.1
	50-59	48	10.6
	60+	12	2.6
	Total	453	100.0
Education	Primary school	16	3.5
	Middle school	83	18.3
	High school	130	28.7
	Bachelor's degree	143	31.6
	Master's degree	70	15.5
	PhD	11	2.4
	Total	453	100.0
Digital assistant usage status	Yes	453	100.0
	No	0	0.0
	Total	453	100.0
Frequency of using digital assistant	Very rare	64	14.1
	Rare	119	26.3
	Few	53	11.7
	Regular	86	19.0
	Increasingly	58	12.8
	A lot	42	9.3
	Always	31	6.8
	Total	453	100.0
Duration of using digital assistant	For the past year.	130	28.7
	For the past 2-3 years	183	40.4
	For the past 4-5 years	92	20.3
	More than 5 years	48	10.6
	Total	453	100.0

Moderation analyses were conducted using the “processR” package (Moon & Hong, 2020) based on Model 1 (Bolin, 2014). Interaction effects, such as CS ~ CE + PT + CE*PT, were tested using mean-centered variables, and conditional effects were examined at –1 SD, M, and +1 SD of the moderator. Visualization and simple-slope plots were generated with the “Interactions” package (Long, 2019) and “ggplot2” (Wickham, 2016).

All coefficients were standardized (β), with standard errors (SE), confidence intervals, and significance levels ($p < .05$).

4. Results

4-1. Measurement Model Assessments

All latent constructs were measured reliably by their observed indicators. Standardized factor loadings ranged from .85 to .95 (see Table 2 and Figure 2), indicating strong convergent validity. Residual variances were low, confirming satisfactory internal consistency for each construct (Hair et al., 2019).

Table 2. Measurement Model Summary

Latent Variable	Indicators	Std. Loadings	Residual Var.
CS	M1_r1 – M1_r4	.85–.93	.14–.28
EXP	M2_r1 – M2_r3	.88–.95	.10–.23
PP	M3_r1 – M3_r3	.89–.93	.14–.21
CE	M4_r1 – M4_r3	.89–.93	.14–.21
CO	M8_r1 – M8_r3	.86–.90	.19–.27
SY	M9_r1 – M9_r3	.89–.91	.17–.21
BD	M10_r1– M10_r3	.89–.92	.16–.21

Notes: CS: Customer Satisfaction, EXP: Expectations, PP: Perceived Performance, CE: Confirmation of Expectations, PT: Perceived Trust, IPC: Privacy Concerns, SE: Self Efficacy, CO: Controllability, SY: Synchronicity, and BD: Bidirectionality.

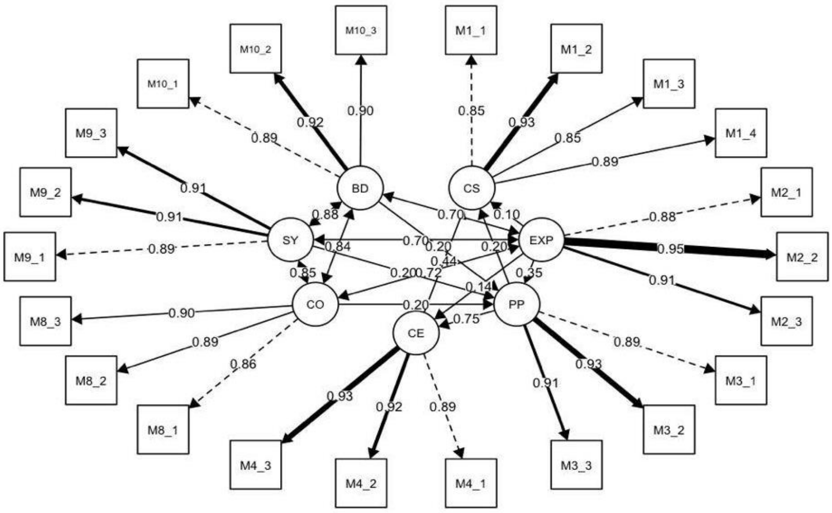

Fig. 2. Measurement Model

4-2. Confirmatory Factor Analysis (CFA)

We conducted a Confirmatory Factor Analysis (CFA) using Maximum Likelihood estimation (ML) on data collected from 453 participants to evaluate a ten-factor measurement model (CS, EXP, PP, CE, PT, IPC, SE, CO, SY, and BD). The model exhibited an excellent fit: χ^2 (389) = 703.99, $p < .001$, CFI = .98, TLI = .98, RMSEA = .042 (90% CI [.037, .047]), and SRMR = .024. After applying robust Yuan–Bentler corrections (Yuan & Bentler, 1997), fit indices further improved: χ^2 (389) = 496.18, $p < .001$, CFI = .99, TLI = .99, RMSEA = .029 (90% CI [.021, .037]), and SRMR = .024. According to Hu and Bentler's (1999) cutoffs, these indices indicate excellent model fit (see Table 3).

All standardized loadings were significant ($p < .001$) and ranged from .65 to .95, exceeding the .50 threshold for practical significance (Hair, 2009). Loadings per construct are presented in Table 4, confirming strong convergent validity across all latent variables.

Table 3. Model Fit Indices for the Confirmatory Factor Analysis

Fit Index	Value	Robust Value	Recommended Cutoff
χ^2 (df = 389)	703.99	496.18	—
CFI	.980	.989	≥ .90 (good), ≥ .95 (excellent)
TLI	.976	.987	≥ .90 (good), ≥ .95 (excellent)
RMSEA	.042 [.037–.047]	.029 [.021–.037]	≤ .06 (good), ≤ .08 (acceptable)
SRMR	.024	.024	≤ .08
AIC	40 481.76	—	—
BIC	40 922.16	—	—

Table 4. Standardized Factor Loadings for the Ten-Factor Model

Latent Construct	Indicators	Standardized Loading (β)	Significance
CS	M1_r1 – M1_r4	.85 – .93	p < .001
EXP	M2_r1 – M2_r3	.88 – .95	p < .001
PP	M3_r1 – M3_r3	.90 – .93	p < .001
CE	M4_r1 – M4_r3	.89 – .93	p < .001
PT	M5_r1 – M5_r3	.90 – .93	p < .001
IPC	M6_r1 – M6_r3	.65 – .91	p < .001
SE	M7_r1 – M7_r3	.87 – .94	p < .001
CO	M8_r1 – M8_r3	.86 – .90	p < .001
SY	M9_r1 – M9_r3	.89 – .91	p < .001
BD	M10_r1 – M10_r3	.89 – .92	p < .001

Notes: CS: Customer Satisfaction, EXP: Expectations, PP: Perceived Performance, CE: Confirmation of Expectations, PT: Perceived Trust, IPC: Privacy Concerns, SE: Self Efficacy, CO: Controllability, SY: Synchronicity, and BD: Bidirectionality.

4-3. HTMT and Discriminant Validity Assessment

Discriminant validity was further assessed using the Heterotrait–Monotrait Ratio (HTMT). Following Henseler et al. (2015), values below .85 indicate conservative discriminant validity and values below .90 are acceptable.

In this study, the HTMT values ranged from .51 to .88, with the highest between SY and BD (.88) (see Table 5). Although this value slightly exceeds the conservative .85 threshold, it remains below the liberal .90 cutoff, indicating acceptable discriminant validity, given the conceptual proximity of the constructs (Ackermans et al., 2023).

Overall, AVE > .50, AVE > MSV, and HTMT < .90 for all constructs demonstrate that the measurement model achieves strong convergent and discriminant validity. The slightly elevated SY–BD HTMT value reflects theoretical overlap rather than empirical redundancy.

4-4. Construct Correlations, Reliability, and Validity Analysis

Descriptive statistics, reliability, and validity indices are presented in Table 5. Mean scores ranged from 4.11 to 4.44 (SD = 0.46–0.74), indicating that participants generally endorsed items at moderately high levels. As can be seen from the upper right corner of Table 5, inter-factor correlations were all positive and significant ($p < .001$), ranging from .54 to .88 (Table 5).

Table 5. Descriptive Statistics, Reliability, and Validity Indices

Construct	M	SD	α	CR	AVE	MSV	CS	EXP	PP	CE	PT	IPC	SE	CO	SY	BD
CS	4.29	0.67	.93	.93	.77	.47	—	.56	.64	.69	.69	.52	.60	.64	.61	.63
EXP	4.44	0.50	.94	.94	.83	.59	.56	—	.77	.72	.75	.74	.67	.73	.70	.70
PP	4.24	0.46	.94	.94	.83	.71	.64	.77	—	.85	.82	.70	.76	.78	.77	.77
CE	4.24	0.46	.94	.94	.83	.71	.68	.71	.84	—	.85	.64	.72	.76	.77	.78
PT	4.12	0.48	.94	.94	.83	.71	.69	.75	.82	.84	—	.70	.82	.83	.83	.85
IPC	4.31	0.74	.85	.86	.69	.56	.54	.75	.72	.66	.72	—	.67	.68	.67	.67
SE	4.11	0.51	.92	.93	.81	.72	.59	.67	.75	.72	.81	.69	—	.86	.79	.80
CO	4.14	0.55	.91	.92	.78	.72	.63	.72	.77	.75	.83	.71	.85	—	.85	.85
SY	4.29	0.46	.93	.93	.82	.78	.60	.70	.77	.77	.83	.70	.78	.85	—	.88
BD	4.29	0.47	.93	.93	.81	.78	.62	.70	.77	.78	.84	.69	.79	.84	.88	—

Note. M = Mean; SD = Standard Deviation; α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance. All HTMT correlations are significant at $p < .001$. AVE > MSV and HTMT < .90 indicate satisfactory discriminant validity. CS: Customer Satisfaction, EXP: Expectations, PP: Perceived Performance, CE: Confirmation of Expectations, PT: Perceived Trust, IPC: Privacy Concerns, SE: Self Efficacy, CO: Controllability, SY: Synchronicity, and BD: Bidirectionality

Although some relationships were moderately high (e.g., SY–BD = .88), none exceeded the .90 threshold, supporting discriminant validity (Fornell & Larcker, 1981). The correlation structure shows that constructs such as Synchronicity, Controllability, and Bidirectionality are conceptually related but empirically distinct, reflecting the multidimensional nature of interactivity in digital assistants.

Cronbach's α values ranged from .85 (IPC) to .94 (PT, PP, EXP), and Composite Reliability (CR) values ranged between .86 and .94, all exceeding the .70 criterion (Alizadeh & Nazapour Kashani, 2023; Hair, 2009). Convergent validity was confirmed with AVE values between .69 and .83, all above the .50 benchmark. Additionally, MSV values were lower than corresponding AVEs, and all HTMT ratios were below .90, confirming discriminant validity (Fornell & Larcker, 1981; Henseler et al., 2015; Iqbal & Khan, 2024). Collectively, these results indicate excellent reliability, strong convergent validity, and satisfactory discriminant validity across all constructs.

4-5. Structural Model Assessments

The structural equation model (SEM) demonstrated excellent fit: χ^2 (194) = 301.94, $p < .001$, CFI = .984, TLI = .981, RMSEA = .035 (90% CI [.029, .041]), SRMR = .044. These indices meet recommended thresholds (CFI/TLI > .95, RMSEA < .06, SRMR < .08), indicating strong overall model adequacy (Ho et al., 2022) (see Table 6).

Table 6. Model Fit and Explained Variance

Fit Index	Value	Threshold	Interpretation
χ^2 (df=194)	301.94	p < .001	Good fit
CFI	0.984	> .95	Excellent
TLI	0.981	> .95	Excellent
RMSEA	0.035	< .06	Excellent
SRMR	0.044	< .08	Excellent
R^2 (CE)	.741	–	High
R^2 (PP)	.734	–	High
R^2 (CS)	.484	–	Moderate-to-strong

Notes: χ^2 = Chi-square statistic; df = degrees of freedom; CFI = Comparative Fit Index; TLI = Tucker–Lewis Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual; R^2 = Squared Multiple Correlation; CE = Confirmation of Expectations; PP = Perceived Performance; CS = Customer Satisfaction.

4-5-1. Hypothesis Testing Results

The hypothesized structural paths and their standardized coefficients are presented in Table 7 and illustrated in Figure 3 Customer Satisfaction (CS) was significantly predicted by Confirmation of Expectations (CE) ($\beta = .44$, $p < .001$) and Perceived Performance (PP) ($\beta = .20$, $p = .042$), while the path from Expectation (EXP) to CS was non-significant ($\beta = .10$, $p = .134$). CE was significantly influenced by PP ($\beta = .75$, $p < .001$), whereas the effect of EXP on CE did not reach statistical significance ($\beta = .14$, $p = .053$). PP was significantly predicted by EXP ($\beta = .35$, $p < .001$), and by three interactivity dimensions: Controllability (CO) ($\beta = .20$, $p = .014$), Synchrony (SY) ($\beta = .20$, $p = .024$), and Bidirectionality (BD) ($\beta = .20$, $p = .027$). The model exhibited considerable predictive validity, explaining the 48% of the variance in CS, 74% in CE, and 73% in PP.

Table 7. Results of the Structural Model and Hypothesis Testing

Hypotheses	Relations	b	Std. β	SE	z	p
H1	EXP → CS	0.105	.098	0.070	1.50	.134 n.s.
H2	EXP → PP	0.317	.348	0.052	6.07	< .001***
H3	PP → CE	0.760	.751	0.071	10.65	< .001***
H4	EXP → CE	0.127	.138	0.066	1.94	.053 n.s.
H5	PP → CS	0.237	.202	0.117	2.03	.042*
H6	CE → CS	0.509	.437	0.104	4.87	< .001***
H10	CO→PP	0.203	.201	0.083	2.45	.014*
H11	SY → PP	0.205	.195	0.091	2.25	.024*
H12	BD → PP	0.195	.199	0.088	2.21	.027*

Notes: *p<0.05; **p<0.01; ***p<0,001; ns: Non-significant. CS: Customer Satisfaction, EXP: Expectations, PP: Perceived Performance, CE: Confirmation of Expectations, PT: Perceived Trust, IPC: Privacy Concerns, SE: Self Efficacy, CO: Controllability, SY: Synchronicity, and BD: Bidirectionality

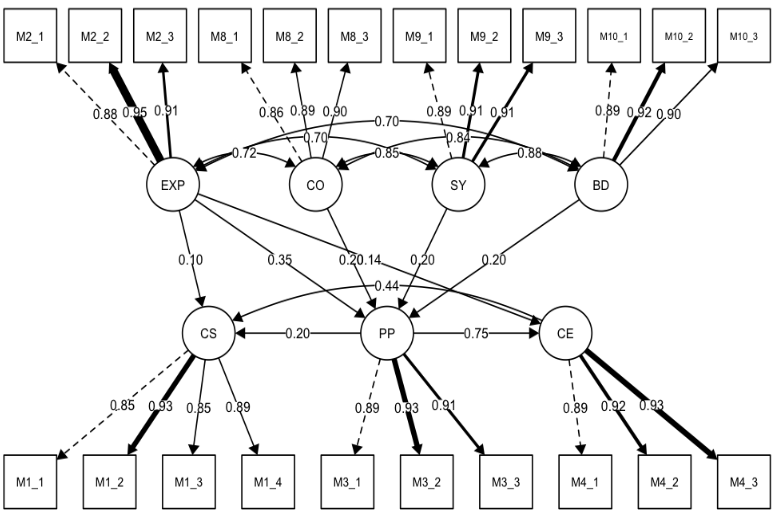

Fig. 3. Structural Model

The results provide robust empirical support for the hypothesized chain Expectation → Perceived Performance → Confirmation of Expectations → Customer Satisfaction**.** CE emerged as the strongest predictor of CS ($\beta = .44$, $p < .001$), followed by PP ($\beta = .20$, $p = .042$).

Moreover, PP was driven by EXP and three interactivity dimensions (CO, SY, and BD), each contributing small-to-moderate positive effects. This pattern indicates that perceived interactivity quality enhances performance perceptions, which subsequently strengthen expectation confirmation and satisfaction.

Overall, the model demonstrates strong explanatory power and theoretical consistency with ECT in service quality and customer experience research.

4-6. Moderation Analysis

Since conventional moderator tests do not provide information about different levels of moderators (e.g., low, moderate, high) and testing moderators in the "lavaan" package requires transforming latent factors into observed variables, we employed the PROCESS analysis as suggested by Bolin (2014) to assess the conditional effects of moderators more precisely.

4-6-1. Moderator Role of Perceived Trust

The overall model was statistically significant, with $F(3, 449) = 134.80$, $p < .001$, explaining 47.4% of the variance in CS ($R^2 = .47$). Both CE ($b = .40$, $p < .001$) and PT ($b = .40$, $p < .001$) exerted significant positive direct effects on CS. The interaction term (CE × PT) was also significant ($b = .08$, $p = .002$), indicating that trust strengthens the CE → CS relationship. As displayed in Table 8, the positive effect of CE on CS becomes stronger as PT increases. The conditional effects analysis shows that when PT is high (+1 SD), the CE → CS slope is steepest ($b = .53$, $p < .001$), while the relationship weakens under low PT (–1 SD; $b = .27$, $p = .001$).

Table 8. Moderator Role of Perceived Trust on the Relationship Between CE and CS

Variable	Coefficient (b)	SE	t	p	LLCI	ULCI
Constant	4.1246	.0814	50.68	< .001***	3.9646	4.2845
CE	.4015	.0629	6.38	< .001***	.2779	.5252
PT	.3983	.0636	6.26	< .001***	.2733	.5234
CE × PT	.0796	.0257	3.10	.002**	.0292	.1301

Model Summary

Statistic	Value	p
R	.688	
R²	.474	
ΔR² (Interaction)	.011	
F(3, 449)	134.80	p < .001***
F(1, 449)	9.64	p = .002 (interaction test)

Conditional Effects of CE on CS at Different Levels of PT

PT Level	b	SE	t	p	LLCI	ULCI
Low PT (–1 SD)	.2734	.0713	3.84	.001**	.1333	.4136
Mean PT	.4015	.0629	6.38	< .001***	.2779	.5252
High PT (+1 SD)	.5296	.0790	6.71	< .001***	.3744	.6848

Notes: *p < 0.05; **p < 0.01; ***p < 0,001; ns: Non-significant. CS: Customer Satisfaction, CE: Confirmation of Expectations, PT: Perceived Trust.

We also conducted a simple slopes analysis (Toothaker, 1994) (see Figure 4), which illustrates that higher perceived trust strengthens the positive relationship between Confirmation of Expectations (CE) and Customer Satisfaction (CS). Specifically, customers with high trust levels experience greater satisfaction gains from confirmed expectations. These results support H7, showing that customers who trust digital assistants more strongly translate confirmation experiences into satisfaction gains.

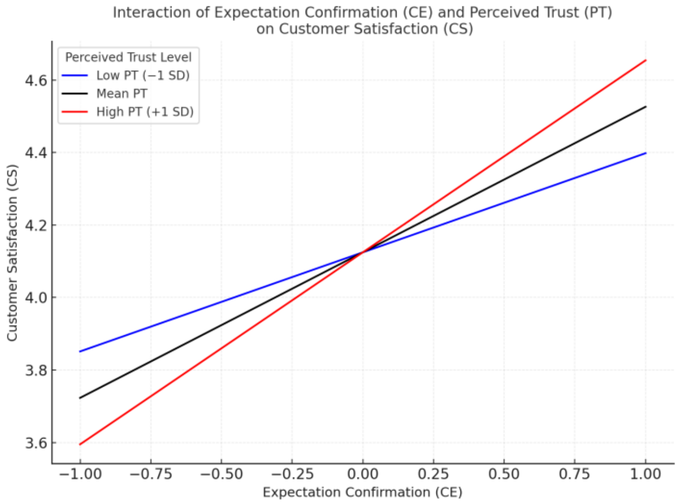

Fig. 4. Interaction Between CE and PT on CS

4-6-2. Moderator Role of Self-efficacy

The second moderation model was significant, with F (3, 449) = 122.47, p < .001, explaining 45.0% of the variance in CS. Both CE (b = .54, p < .001) and SE (SE; b = .26, p < .001) were significant predictors. The interaction (CE × SE) also reached significance (b = .07, p = .006), supporting H8. Conditional effect analysis revealed that CEs impact on CS increases with higher SE. Specifically, when SE is high (+1 SD), CE → CS is strongest (b = .65, p < .001); when SE is low (−1 SD), the relationship weakens (b = .45, p < .001) (see Table 9).

Table 9. Moderator Role of Self-efficacy on the Relationship Between CE and CS

Variable	Coefficient (b)	SE	t	p	LLCI	ULCI
Constant	4.1695	.0764	54.56	< .001***	4.0193	4.3196
CE	.5418	.0523	10.37	< .001***	.4391	.6445
SE	.2568	.0548	4.69	< .001***	.1491	.3644
CE × SE	.0712	.0256	2.78	.006**	.0209	.1215

Model Summary

Statistic	Value	P
R	.671	
R^2	.450	
ΔR^2 (Interaction)	.0095	
F(3, 449)	122.47	p < .001***
F(1, 449)	7.73	p = .006 (interaction test)

Conditional Effects of CE on CS at Different Levels of SE

SE Level	b	SE	t	p	LLCI	ULCI
Low SE (–1 SD)	.4518	.0649	6.64	< .001***	.3034	.5885
Mean SE	.5418	.0523	10.37	< .001***	.4391	.6445
High SE (+1 SD)	.6526	.0665	9.81	< .001***	.5400	.7840

Notes: *p < 0.05; **p < 0.01; ***p < 0,001; ns: Non-significant. CS: Customer Satisfaction, CE: Confirmation of Expectations, SE: Self-efficacy.

As depicted in Figure 5, customers with higher self-efficacy experience a stronger satisfaction boost from confirmed expectations. The red line (+1 SD SE) rises more steeply than the blue line (–1 SD SE), illustrating that confidence in one's ability to use digital assistants enhances the CE–CS relationship. Thus, users who feel more competent at interacting with AI systems derive greater satisfaction when their expectations are met.

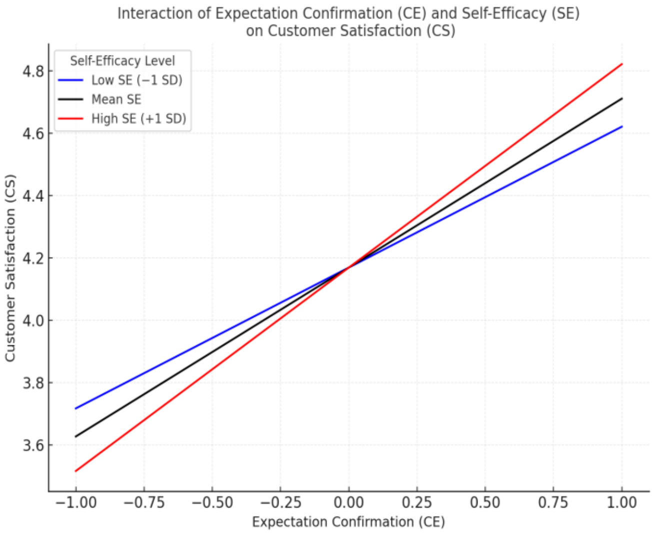

Fig. 5. Interaction Between CE and SE on CS

4-6-3. Moderator Role of Information Privacy Concerns

The third moderation focused on the role of Information Privacy Concerns (IPC) in the relationship between CE and CS. The model was statistically significant, with $F(3, 449) = 110.83$, $p < .001$, explaining 42.6% of the variance in CS ($R^2 = .43$).

Table 10. Moderator Role of Information Privacy Concerns on the Relationship Between CE and CS

Variable	Coefficient (b)	SE	t	p	LLCI	ULCI
Constant	4.2767	.0751	56.97	< .001***	4.1292	4.4243
CE	.6138	.0490	12.52	< .001***	.5174	.7102
IPC	.1778	.0512	3.47	< .001***	.0772	.2783
CE × IPC	.0085	.0261	0.32	.746 n.s.	-.0427	.0597

Model Summary

Statistic	Value	p
R	.652	
R²	.426	
ΔR² (Interaction)	.0001	
F(3, 449)	110.83	p < .001***
F(1, 449)	0.10	p = .746 (interaction test)

Notes: *p<0.05; **p<0.01; ***p<0,001; ns: non-significant. CS: Customer Satisfaction, CE: Confirmation of Expectations, IPC: Privacy Concerns.

Both CE ($b = .61$, $p < .001$) and IPC ($b = .18$, $p < .001$) had positive and significant direct effects on CS. However, the interaction term (CE × IPC) was non-significant ($b = .0085$, $p = .746$), indicating that IPC does not moderate the CE–CS relationship. As shown in Table 10, the conditional effect of CE on CS remains statistically similar across all levels of IPC. In other words, while privacy concerns may influence general perceptions of trust or comfort, they do not impact how expectation fulfillment translates into satisfaction. Therefore, H10 was not supported.

5. Discussion

Customer satisfaction has long been a central focus in marketing research (Brill et al., 2022). This study examined the determinants of customer satisfaction with AI-powered digital assistants, incorporating both cognitive and interactivity-related factors within the expectation–confirmation theory (ECT) framework. R-based structural model explained 48% of the variance in customer satisfaction, 74% in confirmation of expectations, and 73% in perceived performance, indicating strong explanatory power and a robust model fit (CFI = .984, TLI = .981, RMSEA = .035, SRMR = .044).

The results confirmed that Confirmation of Expectations (CE) and Perceived Performance (PP) significantly predicted Customer Satisfaction (CS), while Expectations (EXP) had no direct influence. This finding suggests that users form their satisfaction primarily through post-usage evaluations—how well the assistant performs and whether it meets their expectations—rather than from pre-use assumptions. This pattern aligns with Oliver's (1980) and Bhattacherjee's (2001) post-adoption satisfaction models, which emphasize the primacy of confirmation and performance in satisfaction formation.

In Hypothesis 1, we anticipated a positive relationship between users' expectations of digital assistants and customer satisfaction, driven by the assimilation effect. However, this hypothesis was not supported. Users appear to evaluate digital assistants based on how effectively these tools meet their expectations rather than on their initial anticipations. This result diverges from traditional findings that emphasize fulfilled expectations as a direct driver of satisfaction (Fu et al., 2018; Juliana et al., 2021). For example, Ramasamy et al. (2024) and Oh et al. (2022) both identified expectation confirmation as a crucial determinant of satisfaction across industries. Our finding challenges this assumption, suggesting that in AI-based contexts, satisfaction is more strongly derived from actual system performance and its confirmation, rather than from pre-use expectations. Accordingly, developers should focus on improving digital assistants' functional quality and reliability rather than inflating user expectations.

In Hypothesis 2, we posited a positive relationship between users' expectations of digital assistants and their perceived performance. Our path analysis confirmed this significant correlation. Consistent with previous research (Brill et al., 2022; Lankton & McKnight, 2012), we found that expectations often serve as a benchmark for evaluating performance. These expectations directly influence emotional responses, which can subsequently shape behaviour and performance (Tamir & Bigman, 2018). This phenomenon can lead to an anchoring effect (Epley et al., 2004), where initial expectations significantly impact users' assessments of a digital assistant's actual performance. Given this significant influence, it is essential to manage user expectations through transparent communication and realistic marketing strategies to ensure positive user experiences. Future research could investigate how expectation management techniques affect long-term satisfaction and the continued use of digital assistants.

In Hypothesis 3, we predicted that perceived performance of digital assistants would positively impact confirmation of expectations for digital assistants. Our research findings confirmed this significant relationship, aligning with previous studies (Anderson & Sullivan, 1993; Oliver, 1993). Specifically, when a digital assistant's performance surpasses the user's initial expectations, confirmation of expectations tends to be positive. In contrast, when a digital assistant's performance falls short of expectations, confirmation of expectations tends to be negative. This aligns with the findings of Alnaser et al. (2023), who discovered that expectation confirmation in AI-enabled digital banking is significantly influenced by perceived performance, ultimately enhancing user satisfaction. Similarly, Eren (2021) demonstrated that perceived performance positively impacts expectation confirmation in chatbot banking applications. Considering these findings, managers should prioritize enhancing the performance of digital assistants to consistently meet or exceed user expectations.

In Hypothesis 4, we proposed that users' expectations would positively influence the confirmation of expectations. This relationship was marginally supported ($\beta = .14$, $p = .053$), indicating a weak but positive connection. The result implies that users with higher expectations are somewhat more likely to interpret performance outcomes favorably—a manifestation of the "halo effect" (Brill et al., 2022; Oliver et al., 1994). However, excessive expectations may lead to disappointment when the product cannot meet perceived standards. To avoid this, companies should aim to balance marketing messages with realistic product capabilities, ensuring that expectation management aligns with actual system performance.

In hypothesis 5, we suggested a positive relationship between users' perceived performance of digital assistants and their overall customer satisfaction. This hypothesis was supported ($\beta = .20$, $p = .042$), confirming that user satisfaction depends on how well the digital assistant performs its intended functions. This finding supports the ECT framework (Morgeson, 2012; Park et al., 2012) and prior research, indicating that performance quality directly enhances satisfaction (Tse & Wilton, 1988). In practice, this means that improving operational efficiency, natural language accuracy, and contextual understanding of digital assistants can significantly enhance user satisfaction.

In hypothesis 6, we predicted a positive relationship between the confirmation of users' expectations for digital assistants and overall customer satisfaction. Our findings verified this relationship, demonstrating that many consumers derive satisfaction from the validation of their initial expectations. When users' expectations regarding functionality and usability are confirmed, it strengthens their overall positive evaluation of the servic (Soltani-Nejad et al., 2020). This highlights the importance of maintaining consistent quality and minimizing the gap between expected and perceived outcomes through user-centered design and transparent communication.

In Hypothesis 7, we proposed that perceived trust would positively moderate the relationship between confirmation of expectations and customer satisfaction**.** This hypothesis was supported ($b = .08$, $p = .002$), revealing that higher trust amplifies the positive impact of confirmation on satisfaction. This finding is consistent with previous research emphasizing the role of trust in mitigating risk and enhancing perceived value in AI-based services (Brill et al., 2022; Wu & Dahlan, 2023). Accordingly, digital assistant providers should prioritize data security, reliability, and ethical transparency to strengthen user trust and satisfaction.

In Hypothesis 8, we proposed that self-efficacy would positively moderate the relationship between confirmation of expectations and customer satisfaction. This hypothesis was supported ($b = .07$, $p = .006$), suggesting that higher self-efficacy enhances the translation of confirmed expectations into satisfaction. Users with greater confidence in their ability to operate AI systems derive stronger satisfaction when the system meets their expectations. This result extends previous studies emphasizing the motivational and emotional influence of self-efficacy in technology use (Bravo et al., 2019; Yi & Gong, 2008). Therefore, empowering users through intuitive interfaces and guidance materials may further increase satisfaction among competent, confident users.

In Hypothesis 9, we proposed that information privacy concerns would negatively moderate the relationship between confirmation and satisfaction. This hypothesis was not supported, suggesting that privacy concerns do not significantly weaken satisfaction among users. This outcome may be attributed to optimism bias, where users underestimate potential privacy risks in favor of convenience and functionality (Barth et al., 2022; Maier et al., 2023). Thus, while users may recognize privacy issues, they remain engaged with AI assistants for their perceived utility. Nevertheless, clear privacy communication and responsible data management remain important for sustaining user trust.

In Hypotheses 10–12, we examined the effects of the interactivity dimensions—controllability (CO), synchronicity (SY), and bidirectionality (BD)—on perceived performance (PP). All three hypotheses were supported, indicating that higher interactivity contributes positively to users' perceptions of performance. Specifically, controllability (H10: $\beta = .20$, $p = .014$) and synchronicity (H11: $\beta = .20$, $p = .024$) exerted significant positive effects on perceived performance, suggesting that when users feel they can effectively manage and receive timely responses from digital assistants, they perceive the system as more competent and efficient. Similarly, bidirectionality (H12: $\beta = .20$, $p = .027$) also had a significant positive influence, confirming that reciprocal communication between the user and the assistant enhances perceived functional performance.

These results demonstrate that the perceived quality of interaction directly shapes users' evaluations of system performance, which in turn drives expectation confirmation and satisfaction. This finding aligns with previous research emphasizing the importance of interactive system characteristics in improving user experiences (Purwanto et al., 2020; Yoo et al., 2010). Interactivity creates a sense of engagement and responsiveness that strengthens the user–system relationship, allowing for smoother task completion and greater perceived utility. Hence, developers should equally prioritize features that enhance controllability, synchronicity, and bidirectionality—such as responsive feedback, adaptive command options, and seamless two-way exchanges—to optimize user satisfaction and engagement.

This study extends expectation–confirmation theory by incorporating cognitive (perceived trust, self-efficacy, and information privacy concerns) and interactivity (controllability, synchronicity, and bidirectionality) dimensions to explain satisfaction with AI-powered digital assistants. The R-based results showed that trust and self-efficacy strengthened the link between expectation confirmation and satisfaction, while interactivity dimensions enhanced perceived performance. This indicates that satisfaction is largely driven by performance evaluations supported by user confidence and interactive experience.

Grounded in social cognitive theory (SCT) and protection motivation theory (PMT), the framework clarifies how trust, confidence, and perceived control shape post-adoption satisfaction. Practically, it highlights the need to enhance interactivity quality and transparency to build trust and sustained engagement.

6. Research Implications

6-1. Theoretical Implications

Our study provides several significant contributions to the existing literature. First, it applies and extends the ECT within an AI-interaction context, showing that cognitive and interactivity factors jointly explain satisfaction with digital assistants. By combining ECT, SCT, and PMT, we advance understanding of how expectation confirmation interacts with user confidence, perceived control, and privacy perceptions in shaping satisfaction.

Second, the moderation results identified perceived trust and self-efficacy as significant moderators of the relationship between confirmation and satisfaction, highlighting their critical roles in post-adoption evaluations. This finding aligns with growing evidence that users' trust and perceived competence determine how they translate confirmation experiences into satisfaction (Brill et al., 2022; Lee et al., 2023). However, the non-significant moderation of privacy concerns supports the "privacy paradox," where users prioritize utility and convenience over data apprehensions (Rendina & Mustanski, 2018).

Third, the R-based SEM results confirmed that all three interactivity dimensions—controllability, synchronicity, and bidirectionality—positively affected perceived performance, which subsequently enhanced satisfaction. This reinforces the idea that perceived interactivity quality remains a critical determinant of AI service success (Purwanto et al., 2020). Together, these findings strengthen the theoretical foundation for future research on user–AI interactions, emphasizing the interplay between cognitive beliefs and experiential factors in satisfaction formation.

6-2. Practical Implications

Our findings provide actionable insights for marketers, designers, and developers of AI-based digital assistants seeking to improve user satisfaction.

First, a key factor in optimizing user satisfaction is enhancing interactivity through features such as controllability, synchronicity, and adaptive responses. Digital assistants should enable users to seamlessly navigate conversations, receive immediate feedback, and engage in dynamic, human-like interactions. Customizable voice modulation—allowing users to adjust tone, pitch, and pace—can further personalize the experience, making interactions feel more natural and intuitive. Additionally, AI-driven adaptive responses that adjust based on user behavior, sentiment, and past interactions can foster deeper engagement. For instance, in retail, these enhanced interactivity features can transform shopping experiences by providing real-time, personalized recommendations, thereby giving customers a greater sense of control and satisfaction. To achieve this, companies should prioritize user-centric design, integrating interactive elements that not only improve responsiveness but also proactively enhance the overall customer journey.

Second, establishing and nurturing trust is crucial in all AI interactions. Our study highlights the importance of managers prioritizing trust-building in every customer engagement. This can be achieved through transparency about data usage, robust privacy protections, and consistent, reliable service. In sectors like finance and healthcare, where trust is essential, organizations must ensure that their AI systems are perceived as reliable and secure to foster user confidence. Companies should implement comprehensive communication strategies that clearly outline their privacy practices and security measures to build and maintain trust with users.

Third, although self-efficacy was found to significantly moderate satisfaction, the focus should remain on designing systems that support users' confidence naturally through usability and intelligent guidance, rather than expecting users to self-train. Simplified onboarding, tutorial prompts, and adaptive assistance can encourage continued use without overwhelming users.

Fourth, as AI-driven interactions evolve, businesses should remain agile and responsive to user feedback. Regularly updating systems with enhanced features, emotional responsiveness, and personalized recommendations will ensure sustained engagement and satisfaction. By prioritizing adaptability, transparency, and interactive quality, companies can maintain user trust and strengthen long-term relationships in AI-powered environments.

7. Limitations and Future Research

As with any other empirical investigation, our study has specific limitations that should be recognized when assessing its findings. However, we believe these limitations also present intriguing prospects for future research.

First, our sample consisted exclusively of current users of digital assistants, including some who had recently adopted them. We did not include former users who discontinued their use, as identifying and reaching them posed challenges. Consequently, our study primarily reflects the perspectives of satisfied users, potentially overlooking insights from those who have never engaged with digital assistants or those who have stopped using them. This limitation may distort the interpretation of key relationships among expectation confirmation, perceived performance, and customer satisfaction, missing factors that contribute to user disengagement. To address this gap, we recommend future studies employ a longitudinal approach to track user engagement over time. This method would allow researchers to observe changes in satisfaction, trust, and privacy concerns while capturing the experiences of users who discontinue digital assistants, providing valuable insights into the reasons for disengagement that are often overlooked in cross-sectional studies.

Second, our research focused solely on digital assistant users in Turkey. While this offers meaningful insights into an underrepresented context and helps address the WEIRD bias in academic literature—where studies tend to over-represent Western, educated, industrialized, rich, and democratic populations (Henrich et al., 2010)—it may also introduce sample bias and limit the broader applicability of our results. Cultural norms, socio-economic conditions, and technology usage patterns in Turkey may shape how users perceive digital assistants differently from those in other regions. Therefore, to improve external validity, we encourage future research to examine whether the relationships we observed—particularly those involving interactivity and satisfaction—hold true across diverse cultural and demographic settings.

Third, digital assistants developed by well-established brands—such as Apple's Siri, Amazon's Echo, and Google Home—often benefit from existing consumer trust and positive perceptions of privacy. Future research could investigate how brand trust shapes user expectations, potentially raising standards for performance and security while mitigating privacy concerns. Exploring the link between brand trust and user satisfaction may also offer valuable insights into how positive brand experiences drive long-term adoption and sustained engagement with digital assistants.

Fourth, all three interactivity dimensions—controllability, synchronicity, and bidirectionality—significantly enhanced perceived performance, underscoring the crucial role of interactive communication in shaping user evaluations. Future research could further examine how different forms of bidirectional exchanges (e.g., proactive versus reactive responses) influence satisfaction, especially in contexts with varying levels of privacy awareness.

8. Conclusion

Customer satisfaction remains a central concern in marketing research, and this study contributes by clarifying its formation in AI-driven contexts. Using R-based SEM and moderation analysis, we demonstrated that satisfaction with digital assistants is primarily driven by perceived performance and expectation confirmation, strengthened by users' trust and self-efficacy. Furthermore, controllability, synchronicity, and bidirectionality significantly enhanced perceived performance, underscoring the importance of interactive design. These findings highlight that satisfaction is shaped more by actual experiences and system reliability than by initial expectations or privacy concerns. By emphasizing controllability, bidirectionality, synchronicity, and trust-building mechanisms, organizations can design more effective, transparent, and user-centered AI assistants. Ultimately, our research provides a robust framework for advancing both theoretical and practical understanding of user satisfaction with AI-based technologies.

Data Availability Statement

To ensure transparency and reproducibility, the data and R code used in this study are available from the corresponding author upon reasonable request. Due to privacy and confidentiality considerations, the dataset is not publicly archived; however, all materials can be shared for academic and non-commercial purposes.

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Appendix A

Table A1. Construct Scales

Description	Source
Customer Satisfaction	Brill et al., 2022
Overall, how satisfied are you with your digital assistant?	
Expectations	Lin et al., 2017
Based on my experience so far, I expect that my digital assistant will increase my productivity and improve my performance.	
Based on my experience so far, I expect that my digital assistant will be useful.	
Based on my experience so far, I expect that my digital assistant will allow me to complete tasks more quickly and easily	
Perceived Performance	Lin et al., 2017
Based on my experience with my digital assistant, it increased my productivity and improved my performance.	
Based on my experience with my digital assistant, it was useful.	
Based on my experience with my digital assistant, it allowed me to complete tasks more quickly and easily.	
Confirmation of Expectations	Lin et al., 2017
Thanks to my digital assistant, my increased productivity and performance was ….. than I expected.	
The usefulness of my digital assistant was ….. than expected.	
My ability to complete tasks more quickly and easily with my digital assistant was ….. than I expected.	
Perceived Trust	Komiak & Benbasat, 2006
My digital assistant is like a real expert in providing answers.	
My digital assistant can understand my needs and preferences.	
My digital assistant had good knowledge about the questions and subjects that I am interested in.	
My digital assistant matches my needs to the information available.	
My digital assistant puts my interests first.	
My digital assistant wants to understand my needs and preferences.	
My digital assistant helps me know more about the topic of my inquiry.	
My digital assistant provides unbiased information and recommendations.	
My digital assistant provides honest answers.	
My digital assistant is not linked to a specific company, so it is unbiased.	
Information Privacy Concerns	Kehr et al., 2015
Compared to others, I am more sensitive about the way online companies handle my personal information.	
To me, it is most important to keep my privacy intact from online companies.	
I am concerned about threats to my personal privacy today.	
I believe other people are too much concerned with online privacy issues.	
I am concerned that my digital assistant is collecting too much personal information from me.	
I am concerned that my digital assistant provider will share my personal information with other entities without my authorization.	
I am concerned that unauthorized persons (i. e. hackers) have access to my personal information.	
I am concerned about the privacy of my personal information while using a digital assistant.	
Self-efficacy	Askar & Umay, 2001
I believe I have a special talent for using digital assistants.	
I feel confident when using digital assistants.	
I know what to do when I encounter a new situation in a digital assistant.	
It is easy for me to give any command to a digital assistant.	
I am afraid I might do something wrong when using a digital assistant.	
I have always believed that fully mastering a digital assistant is impossible.	
I feel anxious when using a digital assistant.	
Digital assistants often leave me feeling stuck with no clear solution.	
I believe that I am familiar with the terms and concepts related to digital assistants.	
I think of the digital assistant almost as a part of me.	
I use my digital assistant to plan my day and manage my time.	
I make new discoveries when using my digital assistant.	
I believe I can use digital assistants effectively.	
Most of the time I spend on digital assistants feels unproductive.	
Controllability	Purwanto et al., 2020
I feel a lot of control over this digital assistant application.	
I feel free to do anything with this digital assistant application.	
I gain a lot of experience from this digital assistant application.	
Synchronicity	Purwanto et al., 2020
My digital assistant processes my request quickly.	
I get more information than what I expect from this application.	
I can obtain information immediately without delay.	
Bidirectionality	Purwanto et al., 2020
Digital assistants provide feedback correctly.	
This digital assistant provides the user with the opportunity to interact more freely.	
This digital assistant makes me feel like continuing to use it.	