Journal of
Theoretical and Applied Electronic Commerce Research

MDPI

Article

Perceived AI Anthropomorphism and Brand Loyalty in Generative AI Services: The Roles of Confirmation, Brand Trust, Satisfaction, and Continuance Intention

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Abstract

Generative artificial intelligence services combine functional performance with humanlike interaction, yet it remains unclear whether perceived humanlikeness contributes directly to post-use satisfaction or is associated primarily with more proximal performance and relational appraisals. Drawing on the stimulus–organism–response framework, anthropomorphism theory and the Computers Are Social Actors perspective, the Expectation-Confirmation Model, and consumer–brand relationship research, this study examines perceived AI anthropomorphism (PAIA), confirmation, brand trust, satisfaction, continuance intention, and brand loyalty. Survey data were obtained from 555 ChatGPT users in Türkiye and analyzed using PLS-SEM. PAIA was strongly associated with confirmation ($\beta = 0.624$) and brand trust ($\beta = 0.578$), whereas its direct association with satisfaction was small ($\beta = 0.081$). Confirmation and brand trust were positively associated with satisfaction ($\beta = 0.581$ and $\beta = 0.306$), satisfaction was strongly associated with continuance intention ($\beta = 0.705$), and brand trust, satisfaction, and continuance intention were each positively associated with brand loyalty. Exploratory factor analysis, HTMT diagnostics, and confirmatory comparisons of alternative measurement structures showed substantial overlap between confirmation and satisfaction. The six-construct model fit better than the more parsimonious alternatives examined, but conclusions that depend on separating these two constructs are treated as tentative. Overall, PAIA was strongly associated with post-use and relational appraisals, but whether its association with satisfaction runs mainly through confirmation could not be established with confidence. Because the design is cross-sectional, the findings are interpreted as associations rather than causal effects.

Keywords: generative artificial intelligence; perceived AI anthropomorphism; brand trust; expectation confirmation; continuance intention; brand loyalty

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Academic Editor: Bin Dan

Received: 26 August 2026
Revised: 9 October 2026
Accepted: 12 October 2026
Published: 15 October 2026

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1. Introduction

Generative artificial intelligence services differ from many conventional digital systems because users engage with them through open-ended conversational exchanges rather than fixed menus or predetermined commands. These exchanges can communicate responsiveness, personality, personalization, and apparent social awareness, encouraging users to

interpret the system as more than a purely functional tool. When such interactions occur through an identifiable service such as ChatGPT, perceptions formed during the conversation may also shape evaluations directed toward the service as a brand. The relevant question is therefore not limited to whether users accept or continue using generative AI. It also concerns how humanlike interaction is associated with trust, satisfaction, future usage intentions, and loyalty toward the branded service.

Anthropomorphism refers to the attribution of human characteristics, intentions, or mental states to nonhuman entities [1]. In conversational AI settings, perceptions of personality, humanlike communication, user recognition, and personalized responses may encourage users to interpret the system in social and relational terms. Brand research similarly suggests that anthropomorphic perceptions can influence how consumers evaluate and relate to brands rather than merely how they assess product functionality [2]. In voice-based AI contexts, Patrizi et al. [3] found that brand anthropomorphism was positively associated with brand trust and consumer–brand engagement. More recently, Hussain [4] showed that anthropomorphic attributes of generative AI brands were related to brand respect and brand heroism. Together, these studies indicate that anthropomorphism can extend beyond interface evaluation and become relevant to brand-level relational outcomes.

Nevertheless, the consequences of anthropomorphism are not uniformly positive or necessarily direct. Humanlike design is often expected to improve user responses, and meta-analytic evidence indicates that anthropomorphism is, on average, positively associated with customers' intentions to use service technologies; however, the magnitude and direction of these effects vary across conditions [5]. Experimental evidence also identifies boundary conditions and unfavorable responses. Crolic et al. [6] showed that anthropomorphism can reduce customer satisfaction when users enter chatbot interactions in an angry state, because humanlike agents can raise expectations of efficacy that are subsequently violated. Kim et al. [7] found that anthropomorphizing consumer robots increased perceived warmth while decreasing liking. In post-use chatbot contexts, Rita et al. [8] likewise found that some forms of perceived humanness were more consequential than generic anthropomorphic cues. These findings suggest that perceived humanlikeness may not operate as a uniformly positive direct antecedent of satisfaction.

This evidence points to a more specific theoretical problem than whether anthropomorphism is beneficial. A direct-effect account treats perceived humanlikeness as a potential source of satisfaction in its own right. An upstream-appraisal account instead proposes that perceived humanlikeness is associated more strongly with proximal performance and relational appraisals—particularly confirmation and brand trust—which are then associated with satisfaction and downstream outcomes. Existing research provides limited evidence comparing these accounts within the same post-use model. The present study therefore examines whether the observed pattern of associations is more consistent with a direct-effect account or with an upstream-appraisal account, while recognizing that a cross-sectional design cannot establish temporal or causal ordering.

The Expectation-Confirmation Model provides an appropriate foundation for explaining the performance-based part of this process. The model proposes that users evaluate a system after adoption by comparing their experience with their prior expectations. Confirmation contributes to satisfaction, which subsequently supports continuance intention [9]. This logic remains influential because continued use depends not only on beliefs formed before adoption but also on evaluations derived from actual experience. Recent research has extended expectation-confirmation reasoning to AI-enabled services. Chau et al. [10], for example, examined confirmation, satisfaction, continuance usage intention, and purchase intention in the context of AI-powered e-commerce customer service. Their study demon-

strates the relevance of expectation fulfilment and satisfaction to sustained engagement with AI services.

Expectation-confirmation research, however, generally begins with users' assessments of whether a system has met their expectations. It gives less attention to how socially meaningful perceptions formed during interaction may shape confirmation itself. Conversely, anthropomorphism research often examines trust, satisfaction, engagement, or symbolic brand outcomes without locating anthropomorphic perceptions within a post-adoption evaluation sequence. The two research streams therefore offer complementary but incomplete explanations. Expectation-confirmation studies clarify how experience is related to satisfaction and continuance intention, while anthropomorphism studies explain why an AI interface may be perceived in social or relational terms. What remains less clear is how anthropomorphic perceptions enter the expectation-confirmation process and whether they are concurrently associated with a relational assessment of the brand.

Brand trust is particularly important in addressing this limitation. Trust in an AI agent and trust in the brand represented by that agent are related but conceptually distinct. Agent-level trust concerns whether the immediate technological system appears competent or dependable. Brand trust reflects confidence in the reliability of the brand and in its intentions toward the consumer. This distinction is especially relevant for generative AI because the conversational interface is the principal point at which users encounter the service and form impressions of the brand behind it. Evidence from voice assistants indicates that anthropomorphic brand perceptions can be associated with brand trust, while research on ChatGPT has linked trust with satisfaction and continuance intention [3,11]. Research on AI-chatbot service quality has also positioned user trust as a mechanism associated with e-brand loyalty [12].

A further conceptual issue concerns the outcomes used to represent a continuing relationship with AI. Much of the post-adoption literature focuses on continuance intention, reuse intention, retention, or loyalty to chatbot usage. These outcomes capture users' willingness to maintain interaction with a system, but they do not necessarily represent loyalty toward the brand. Users may intend to continue using an AI service because it is convenient, familiar, accessible, or integrated into their routines. Brand loyalty involves a broader orientation that may include first preference, recommendation, resistance to functionally similar alternatives, and attachment to the brand. Rita et al. [8] examined loyalty to chatbot usage, while Chau et al. [10] focused on continuance and purchase intention. Hussain [4], in contrast, examined the more symbolic and advocacy-oriented outcome of brand heroism. These studies provide important but different accounts of sustained user–AI relationships and underline the need to distinguish future system use from loyalty toward an AI service as a brand.

Accordingly, the literature gap addressed by the present study does not arise because anthropomorphism, confirmation, trust, satisfaction, continuance intention, or loyalty have been entirely overlooked. The unresolved issue concerns the role that perceived humanlikeness plays within post-use evaluation. Prior studies often treat anthropomorphism as a direct antecedent of satisfaction or as a source of symbolic and relational brand responses, whereas expectation-confirmation research typically begins with users' assessments of whether the service met prior expectations. It therefore remains unclear whether perceived humanlikeness contributes primarily through a direct satisfaction route or through more proximal performance and relational appraisals. A related gap concerns the distinction between intention to maintain system use and loyalty toward the branded service. The present study addresses these issues jointly while keeping interaction-, service-, and brand-level constructs conceptually distinct.

The research problem is therefore the incomplete understanding of how perceived humanlike characteristics formed during interaction with a branded generative AI service are associated with both post-use performance evaluations and consumer–brand relationship outcomes. Three recent streams illustrate the separation: GenAI brand-anthropomorphism research emphasizes symbolic brand outcomes (e.g., [4]), expectation-confirmation research emphasizes confirmation, satisfaction, and continued use (e.g., [10]), and chatbot research links service characteristics with satisfaction and usage-oriented loyalty (e.g., [8]). The present study examines these accounts within one model without treating ChatGPT as a representative proxy for all generative AI services.

Against this background, the study addresses the following overarching research question:

RQ: How is perceived AI anthropomorphism during interaction with ChatGPT associated with performance-based confirmation and brand-level trust, and how are these evaluations related to satisfaction, continuance intention, and brand loyalty?

The primary aim of the study is to examine how perceived AI anthropomorphism is associated with confirmation and brand trust and how these evaluations relate to satisfaction, continuance intention, and brand loyalty in the context of ChatGPT. More specifically, the study aims to:

1. assess the relationships of perceived AI anthropomorphism with confirmation, brand trust, and satisfaction;
2. examine how confirmation and brand trust are related to satisfaction and continuance intention;
3. evaluate the direct and indirect relationships through which brand trust, satisfaction, and continuance intention are associated with brand loyalty;
4. examine continuance intention and brand loyalty as related but conceptually distinct outcomes.

The study contributes to the literature in four principal ways. First, it reframes the focal construct as perceived AI anthropomorphism (PAIA), an interaction-level perception rather than anthropomorphism of the brand itself. Second, it uses the stimulus–organism–response (S-O-R) framework to organize anthropomorphism theory/CASA, the Expectation-Confirmation Model, and consumer–brand relationship research within a single post-use model. Third, it compares a direct-effect account with an upstream-appraisal account by examining PAIA simultaneously in relation to confirmation, brand trust, and satisfaction. Fourth, it distinguishes continuance intention from brand loyalty, thereby separating future system use from a broader brand-level orientation involving preference, recommendation, resistance to comparable alternatives, and attachment. The contribution is therefore a pattern of theoretically linked associations rather than a claim that the individual constructs are new.

The proposed model is examined using survey data from 555 individuals in Türkiye who had previously used ChatGPT. Partial least squares structural equation modeling is used to assess the measurement model, test the proposed structural relationships, and examine the specific indirect effects connecting anthropomorphic perceptions with post-use and brand-level outcomes.

2. Literature Review and Hypothesis Development

2.1. Theoretical Foundations

The model is organized using the stimulus–organism–response (S-O-R) framework [13,14]. In this structure, perceived AI anthropomorphism (PAIA) is treated as a perceived interactional stimulus; confirmation, brand trust, and satisfaction are internal post-use appraisals; and continuance intention and brand loyalty are response outcomes. S-

O-R provides the overarching logic, while more specific theories explain the content of each stage. The unit of analysis is the individual user, but the focal object differs across constructs: PAIA concerns the conversational agent encountered during interaction; confirmation, satisfaction, and continuance intention concern the ChatGPT service/use relationship; and brand trust and brand loyalty concern ChatGPT as an identifiable brand.

PAIA refers to the extent to which users attribute humanlike characteristics to the conversational agent through which they interact with ChatGPT. It does not imply that users literally believe the system is human. Anthropomorphism theory explains how people apply human schemas to nonhuman entities [1], while the Computers Are Social Actors perspective shows that people can apply social responses to computers displaying social cues even when they know they are interacting with machines [15]. In the present measure, humanlike characteristics include perceived personality, humanlike responding and communication, increasing familiarity, and personalization. These perceptions are narrower than general interaction quality because they concern humanlike attribution rather than whether the service is simply useful, accurate, or satisfactory. Some GenAI studies use the broader label brand anthropomorphism (e.g., [4]); because the administered items describe the conversational agent encountered during interaction, the present study uses the narrower term perceived AI anthropomorphism.

The performance-based part of the model is grounded in the Expectation-Confirmation Model (ECM). Originating in satisfaction research [16] and adapted to information-system continuance by Bhattacherjee [9], ECM proposes that users compare experienced performance with prior expectations. Confirmation is therefore a cognitive comparison of expected and experienced performance, whereas satisfaction is an overall post-use evaluation. Satisfaction, in turn, is associated with future continuance intention. This distinction is theoretically important in the present study because confirmation and satisfaction are adjacent but conceptually non-equivalent post-use appraisals.

The model also includes a relationship-based route. Consumer–brand relationship research conceptualizes brands as relationship partners rather than as purely functional identifiers [17]. Brand trust reflects confidence in the reliability of the brand and in its intentions toward the consumer [18]. Interaction with a branded conversational agent can provide information that users carry into evaluations of the organization or service represented by that agent [19,20]. Brand loyalty is broader than a plan to reuse the service: in this study it encompasses first preference, recommendation, preference over comparable alternatives, and an attachment component. Continuance intention and brand loyalty are therefore treated as related but distinct response outcomes.

Within this S-O-R structure, the study compares two accounts of PAIA. The direct-effect account predicts that perceived humanlikeness itself is associated with satisfaction. The upstream-appraisal account predicts that PAIA is more strongly associated with confirmation and brand trust, which are then related to satisfaction and downstream outcomes. The cross-sectional design does not identify a causal sequence; rather, the specified structural model tests whether the observed associations are more consistent with one account than the other. Figure 1 summarizes the resulting model.

2.2. Hypothesis Development

2.2.1. Perceived AI Anthropomorphism, Confirmation, Satisfaction, and Brand Trust

Humanlike cues may shape how users interpret the performance of a generative AI service. Humanlike cues can also make system behavior easier to interpret through familiar social schemas [1,21]. Anthropomorphic design does not necessarily improve evaluations in every setting: Crolic et al. [6] showed that humanlike chatbot cues can heighten efficacy expectations and backfire when those expectations are violated, particularly when

customers are angry. That evidence concerns anthropomorphic design cues encountered before or during an interaction, whereas PAIA in the present study is a post-use perception reported after experience with ChatGPT. In this post-use setting, an interaction perceived as more humanlike, responsive, and personalized may be judged as more consistent with what users expect from an intelligent conversational service. Confirmation remains a distinct post-use comparison between expected and experienced performance; PAIA is therefore expected to be positively associated with confirmation.

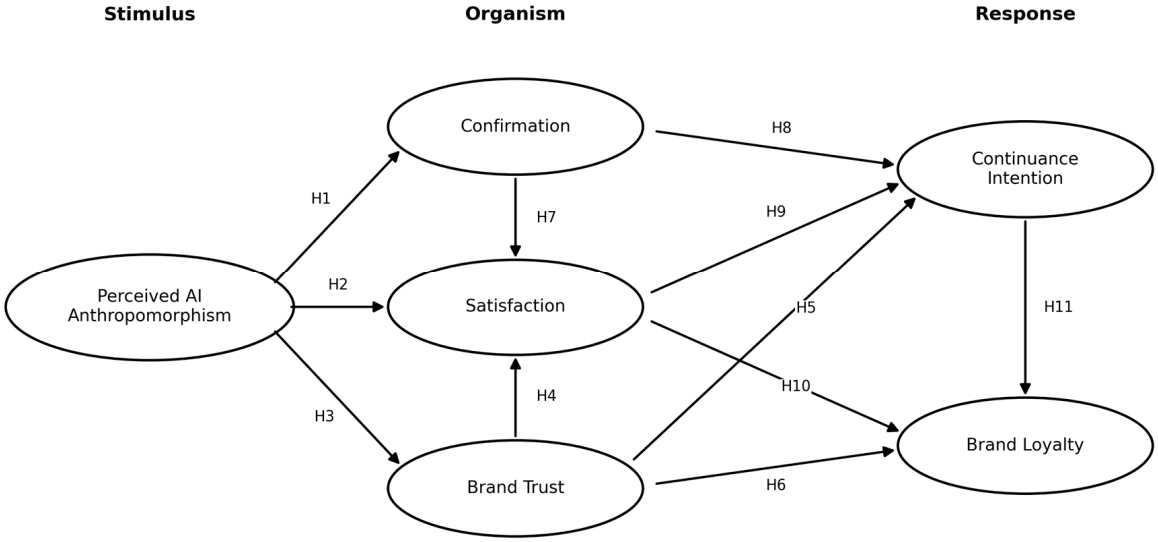


Figure 1. Conceptual research model organized using the S-O-R framework.

H1. *Perceived AI anthropomorphism is positively associated with confirmation.*

Perceived humanlikeness may also be directly associated with satisfaction. Meta-analytic evidence generally identifies favorable average responses to anthropomorphism, but the relationship is contingent rather than uniformly positive [5]. Seo [22], for example, linked anthropomorphism to customer satisfaction in service-robot settings, whereas Crolic et al. [6] demonstrated that anthropomorphism can reduce satisfaction when angry customers interact with chatbots. Kim et al. [7] likewise showed that humanizing consumer robots can increase warmth while decreasing liking. These findings support testing a direct PAIA–satisfaction relationship while also motivating the competing possibility that perceived humanlikeness is associated primarily with more proximal appraisals.

H2. *Perceived AI anthropomorphism is positively associated with satisfaction.*

Anthropomorphic perceptions can also influence trust judgments. Users frequently infer competence, benevolence, and integrity from the social and communicative behavior of an interaction partner. When the conversational interface is the principal point of contact with an identifiable AI service, these inferences can become associated with the brand represented by that interface. Evidence from chatbot, voice-assistant, and generative AI settings indicates that anthropomorphic characteristics are related to trust and other brand-level relational responses [3,23]. Agent trust and brand trust remain conceptually distinct, but repeated interaction with the branded agent provides information from which users may evaluate the reliability and integrity of the ChatGPT brand.

H3. *Perceived AI anthropomorphism is positively associated with brand trust.*

2.2.2. Brand Trust and Post-Use Outcomes

Trust provides a relational basis for interpreting experience under uncertainty. Users who regard the ChatGPT brand as reliable and as acting in a manner they can depend on are likely to evaluate their experiences more favorably. In chatbot settings, Eren [24] provides direct evidence of a positive trust–satisfaction relationship. Brand trust should therefore complement performance-based confirmation by capturing confidence in the branded service behind the interaction.

H4. *Brand trust is positively associated with satisfaction.*

Trust can also support continuance intention because it reduces the perceived uncertainty attached to future interactions. In digital services, users are more willing to maintain a relationship when they believe the provider will continue to act reliably and competently [25]. This consideration is particularly salient for generative AI, where response quality can vary across tasks and occasions. Users who trust the ChatGPT brand should consequently report stronger intentions to continue using the service.

H5. *Brand trust is positively associated with continuance intention.*

Brand trust is a well-established antecedent of loyalty because confidence in a brand's reliability and integrity can strengthen preference and reduce willingness to switch [26,27]. In chatbot research, user trust has also been linked to e-brand loyalty [12]. In the present setting, trust is expected to be relevant not only to future use but also to loyalty toward ChatGPT as a branded generative AI service.

H6. *Brand trust is positively associated with brand loyalty.*

2.2.3. Confirmation, Satisfaction, and Continuance Intention

Confirmation is a central antecedent of satisfaction in ECM. When experienced performance meets or exceeds prior expectations, users are more likely to evaluate the service positively [9,16]. This relationship has been repeatedly supported in technology-continuance research, including AI-powered service settings [28–30]. Users who believe that ChatGPT has delivered the expected level of usefulness and performance should therefore report higher satisfaction.

H7. *Confirmation is positively associated with satisfaction.*

ECM primarily explains the effect of confirmation on continuance through satisfaction and post-use beliefs. Some extended models have nevertheless included a direct confirmation–continuance path and found that expectation fulfilment can also retain an independent relationship with future use [29]. Because ChatGPT can be used across varied personal, academic, and professional tasks, confirmation may directly strengthen the intention to return to the service even after satisfaction is considered. This path is therefore treated as an additional relationship rather than a defining component of the original ECM.

H8. *Confirmation is positively associated with continuance intention.*

Satisfaction summarizes users' evaluation of their accumulated experience and is one of the most consistent predictors of information-system continuance [9,30,31]. Satisfied users are more likely to preserve their relationship with a service because their prior

interactions provide a favorable basis for future use. Accordingly, satisfaction should be positively associated with the intention to continue using ChatGPT.

H9. *Satisfaction is positively associated with continuance intention.*

Satisfaction can also contribute to loyalty at the brand level. Oliver [32] treats satisfaction as an important but insufficient condition for loyalty, while e-loyalty research shows that favorable post-use evaluations can coexist with other relational and market determinants [33]. In the present context, users who evaluate their ChatGPT experience positively are expected to report stronger loyalty toward the brand, without implying that satisfaction alone constitutes loyalty.

H10. *Satisfaction is positively associated with brand loyalty.*

2.2.4. Continuance Intention and Brand Loyalty

Continuance intention and brand loyalty are related but not interchangeable. Continuance intention concerns the prospective decision to keep using a system, whereas brand loyalty reflects a broader preference and commitment toward the branded service. Repeated future use may accumulate experience and familiarity that accompany stronger brand preference, but continuance intention is not itself loyalty. Users who plan to continue using ChatGPT are therefore expected to report stronger loyalty toward the ChatGPT brand, while the cross-sectional design does not imply a temporal progression from one construct to the other.

H11. *Continuance intention is positively associated with brand loyalty.*

3. Methodology

3.1. Research Design and Data Collection

A quantitative, cross-sectional online survey was used to examine the proposed relationships among perceived AI anthropomorphism, confirmation, brand trust, satisfaction, continuance intention, and brand loyalty. The unit of analysis was the individual ChatGPT user. ChatGPT was treated as an analytically important case of an identifiable generative AI service rather than as a statistically representative proxy for all generative AI services. ChatGPT is relevant because users encounter a persistent conversational interface under a recognizable service identity, so interaction-level perceptions and brand-level evaluations arise within the same use setting. At the interaction level, PAIA concerns the conversational agent; at the service/use level, confirmation, satisfaction, and continuance intention concern users' experience with ChatGPT; and at the brand level, brand trust and brand loyalty concern the identifiable ChatGPT brand. The target population comprised individuals in Türkiye who had previously used ChatGPT.

Because no complete sampling frame of ChatGPT users was available, convenience sampling was employed. The questionnaire was administered through Google Forms (Google LLC, Mountain View, CA, USA; https://forms.google.com), and the link was distributed through the authors' social media networks. An initial screening question asked whether respondents had previously used ChatGPT; only those who answered affirmatively were allowed to proceed with the survey. The analytical dataset comprised 555 responses collected between 31 October 2025 and 5 February 2026. All 555 responses collected during the designated analytical period were retained.

Before participation, respondents were informed about the purpose of the study, the voluntary nature of participation, and the confidentiality of their responses. Informed

consent was obtained before respondents proceeded to the questionnaire. No personally identifying information was collected.

3.2. Questionnaire Development and Measures

The questionnaire consisted of demographic questions and 24 measurement items. Items were adapted or contextually developed from established construct definitions and prior scales and were contextualized for ChatGPT. Responses were recorded on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). All constructs were specified as reflective. Appendix A reports the Turkish wording administered to respondents together with its English equivalent and the source/provenance information used for each item.

Perceived AI anthropomorphism was measured using six items adapted from the anthropomorphism dimension of Noor et al.'s [34] service-quality scale for artificial intelligence service agents. The items capture perceived humanlike characteristics, personality, increasing familiarity with the user, humanlike responding, personalization, and humanlike communication. The manuscript retains the analytical item labels AIBA1–AIBA6 for traceability to the original dataset, although the construct is labelled PAIA throughout the text.

Because the items describe the conversational agent encountered during interaction, PAIA is treated as an interaction-level perception rather than anthropomorphism of the brand itself. The transition to brand-level outcomes is modeled through downstream brand trust and brand loyalty: impressions formed through a conversational agent can influence evaluations of the organization or brand represented by that agent [19].

Brand trust was assessed with four contextually adapted items informed by the brand-trust literature, including Delgado-Ballester [18] and Ghorbanzadeh et al. [23]. The items cover response reliability, ethical and secure data handling, openness about mistakes or limitations, and trust in the performance of the ChatGPT brand. Confirmation and continuance-intention items were contextualized from Bhattacherjee's [9] ECM measures. The satisfaction items operationalize the ECM satisfaction construct in the ChatGPT context; SAT4 ("Choosing to use ChatGPT was a wise decision") was adapted from Noor et al. [34]. In CI1–CI2, "the ChatGPT brand" was used in the Turkish questionnaire as the name of the service; continuance intention is interpreted here as intention to maintain the use relationship.

Brand loyalty was assessed with four indicators covering first-choice preference, recommendation, preference over comparable alternatives, and emotional attachment. The first-choice, recommendation, and comparable-alternative items were contextually adapted from established brand-equity, loyalty, and preference measures [35,36]. BL4 was a study-specific item included to capture the attachment component of the construct. Because its loading was comparatively low, its influence was examined in a sensitivity analysis reported in Appendix C.

The items were translated or prepared in Turkish and subsequently reviewed by three marketing professors for clarity, comprehensibility, and contextual appropriateness. Following this review, the questionnaire wording was retained without further modification.

3.3. Data Analysis

The proposed model was analyzed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS (version 3.2.9; SmartPLS GmbH, Bönningstedt, Germany), following established reporting guidance [37]. An exploratory factor analysis (EFA) was additionally conducted in IBM SPSS Statistics (version 24; IBM Corp., Armonk, NY, USA) to examine the empirical dimensionality of the measurement items outside the PLS-SEM

environment. Principal axis factoring with oblique Promax rotation was used because the constructs were theoretically expected to correlate [38]. Sampling adequacy was evaluated using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity, and parallel analysis based on principal-component eigenvalues from 1000 random datasets was used to inform factor retention [39]. Two additional retention criteria were examined: common-factor parallel analysis using the reduced correlation matrix with squared multiple correlations on the diagonal [40], and Velicer's component-based minimum average partial (MAP) test [41]. To examine whether fewer, empirically derived constructs would represent the data better than the theory-specified structure, the six-factor measurement model was also compared with alternative structures using confirmatory factor analysis in R (version 4.3.3; R Foundation for Statistical Computing, Vienna, Austria) using the lavaan package (version 0.6-17) [42]. Robust maximum likelihood (MLR) was the primary estimator, and weighted least squares mean- and variance-adjusted estimation (WLSMV), with the items treated as ordinal, served as a sensitivity check [43]. These factor-based analyses complement the composite-based PLS-SEM estimation rather than replace it.

The PLS-SEM analysis proceeded in two stages. First, the reflective measurement model was evaluated using indicator loadings, Cronbach's alpha, rho_A, composite reliability, and average variance extracted (AVE). Discriminant validity was assessed using the Fornell–Larcker criterion [44], indicator cross-loadings, the heterotrait–monotrait ratio (HTMT) with bootstrap confidence intervals [45], HTMT2 [46], and comparisons of AVE with maximum and average shared variance (MSV and ASV). Second, the structural model was assessed using standardized path coefficients, t-values, *p*-values, coefficients of determination (R^2), effect sizes (f^2), and inner-model variance inflation factors (VIFs). SmartPLS fit statistics were reported as supplementary diagnostics. Statistical significance was assessed using bootstrapping with 5000 subsamples. Specific indirect effects were examined for the intervening relationships specified in the model. A sensitivity model in which confirmation and satisfaction were combined into a single construct was also estimated (Appendix C). Out-of-sample predictive performance was assessed using PLSpredict with 10-fold cross-validation and 10 repetitions [47]. Because the study is cross-sectional, structural paths are interpreted as associations rather than definitive evidence of causality.

3.4. Common Method Considerations

Several procedural measures were used to reduce potential common method concerns. Participation was anonymous, respondents were informed that their responses would remain confidential, and the questionnaire used concise and clearly worded items. Harman's single-factor test was conducted as a supplementary diagnostic by entering all 24 measurement items into a principal axis factoring analysis constrained to a single unrotated factor. The extracted factor accounted for 50.695% of the total variance. Harman's procedure does not distinguish substantive covariance from method variance and cannot establish either the presence or the absence of common method bias by itself [48]. The result is therefore reported transparently.

Following Kock and Dow [49], full-collinearity VIFs were also computed for all six constructs from the PLS construct scores: 1.90 (PAIA), 3.82 (confirmation), 6.13 (satisfaction), 2.90 (brand trust), 3.92 (continuance intention), and 3.27 (brand loyalty). Each construct score was regressed on the other five construct scores, and its VIF was calculated as $1/(1 - R^2)$. Confirmation, satisfaction, and continuance intention exceeded the 3.3 threshold recommended for composite-based SEM analyses [49]. Accordingly, the full-collinearity diagnostic does not support a conclusion that the model is free from common method bias under this criterion. Because the elevated values are concentrated among theoretically adjacent post-use constructs, the result is interpreted cautiously. These diagnostics leave

common method concerns unresolved and therefore constrain the interpretation of the observed associations.

3.5. Ethics Statement

Ethical approval for the study was granted by the Fırat University Social and Human Sciences Research Ethics Committee on 30 October 2025 (Meeting No. 2025/23, Decision No. 33). Participation was voluntary, and informed consent was obtained before respondents proceeded to the questionnaire.

4. Results

4.1. Sample Characteristics

The analytical sample comprised 555 participants. Women represented 53.7% of the sample, while men accounted for 46.3%. Participants were predominantly young adults: 38.9% were aged 18–25 and 27.2% were aged 26–35. Taken together, 66.1% of respondents were between 18 and 35 years of age.

Regarding education, 42.0% of participants held a bachelor's degree, 12.4% held a master's degree, and 2.7% held a doctoral degree. Students constituted the largest occupational group at 30.8%, followed by private-sector employees at 29.4% and public-sector employees at 20.7%. The complete demographic profile is presented in Table 1.

Table 1. Sample characteristics (N = 555).

Variable	Category	*n*	%
Gender	Male	257	46.3
	Female	298	53.7
Age	18–25	216	38.9
	26–35	151	27.2
	36–45	111	20.0
	46–55	62	11.2
	56 and above	15	2.7
Education	High school or below	148	26.7
	Associate degree	90	16.2
	Bachelor's degree	233	42.0
	Master's degree	69	12.4
	Doctoral degree	15	2.7
Monthly income (TRY)	Minimum wage or below	134	24.1
	28,076–35,000	90	16.2
	35,001–50,000	72	13.0
	50,001–75,000	133	24.0
	75,001 or above	126	22.7
Occupation	Public-sector employee	115	20.7
	Private-sector employee	163	29.4
	Student	171	30.8
	Retired	15	2.7
	Other	91	16.4
Total		555	100.0

4.2. Measurement Model and Exploratory Assessment

4.2.1. Exploratory Factor Analysis

An exploratory factor analysis was conducted in IBM SPSS Statistics using principal axis factoring with Promax rotation. The Kaiser–Meyer–Olkin measure was 0.962, and Bartlett's test of sphericity was significant, $\chi^2(276) = 10{,}203.730$, $p < 0.001$, indicating that the correlation matrix was suitable for factor analysis. Parallel analysis based on principal-component eigenvalues from 1000 random datasets suggested three broader empirical

dimensions: the first three observed eigenvalues (12.604, 1.578, and 1.425) exceeded the corresponding 95th-percentile random eigenvalues (1.457, 1.381, and 1.324), whereas the fourth observed eigenvalue (0.901) did not exceed its random benchmark (1.277) (Table 2). Because the number of factors suggested by parallel analysis can depend on whether principal-component or common-factor eigenvalues are used [40], the two additional criteria described in Section 3.3 were also examined. Common-factor parallel analysis and Velicer's MAP test [41] both suggested four factors.

Table 2. Parallel-analysis results used to inform factor retention.

Component	Observed Eigenvalue	95th-Percentile Random Eigenvalue	Retain?
1	12.604	1.457	Yes
2	1.578	1.381	Yes
3	1.425	1.324	Yes
4	0.901	1.277	No

The exploratory solutions did not reproduce the six theory-specified constructs as six clean empirical factors. In the three-factor solution, confirmation, satisfaction, continuance-intention, and several brand-related indicators formed a broad post-use factor, while most PAIA indicators clustered on a second factor; AIBA2, however, loaded slightly more strongly on the brand-relational factor than on the PAIA factor. In the forced six-factor solution, confirmation clustered with SAT1–SAT3, SAT4 clustered with continuance-intention indicators, PAIA indicators showed internal differentiation between humanlike communication/behavior and personalization/familiarity, BL3 and BL4 loaded with the brand-trust indicators, and BL1 and BL2 formed a separate factor. In the four-factor solution suggested by these two criteria, CON1–CON3 and SAT1–SAT3 formed one factor, the PAIA indicators a second, the brand-trust indicators together with BL4 a third, and the continuance-intention indicators together with SAT4, BL1, and BL2 a fourth; BL3 loaded on both the third and fourth factors. The three-factor and forced six-factor pattern matrices are reported in Tables A2 and A3; the dominant groupings of the four-factor solution are summarized above and specified in the notes to Table A4. EFA was used diagnostically rather than to redefine the theory-specified PLS-SEM measurement model; the results instead motivated the more extensive discriminant-validity assessment and the comparison of alternative measurement structures reported below (Sections 4.2.4 and 4.2.5).

4.2.2. Reliability and Convergent Validity

Indicator loadings ranged from 0.577 to 0.928, with most exceeding 0.70. AIBA2 (0.589) and BL4 (0.577) were lower, but both were retained on substantive measurement grounds because the corresponding constructs maintained acceptable composite reliability and AVE and the indicators contributed to intended content coverage [37]. Cronbach's alpha ranged from 0.782 to 0.927, rho_A from 0.835 to 0.927, composite reliability from 0.860 to 0.948, and AVE from 0.552 to 0.838, supporting convergent validity at the construct level (Table 3).

Table 3. Reflective measurement-model results.

Construct/Item	Loading	α	rho_A	CR	AVE
PAIA		0.835	0.844	0.880	0.552
AIBA1	0.754				
AIBA2	0.589				
AIBA3	0.768				
AIBA4	0.797				

Table 3. *Cont.*

Construct/Item	Loading	α	rho_A	CR	AVE
AIBA5	0.730				
AIBA6	0.798				
Confirmation		0.881	0.885	0.926	0.807
CON1	0.905				
CON2	0.878				
CON3	0.912				
Satisfaction		0.927	0.927	0.948	0.820
SAT1	0.927				
SAT2	0.928				
SAT3	0.897				
SAT4	0.869				
Brand trust		0.862	0.873	0.906	0.706
BT1	0.851				
BT2	0.806				
BT3	0.823				
BT4	0.879				
Continuance intention		0.903	0.904	0.939	0.838
CI1	0.918				
CI2	0.920				
CI3	0.909				
Brand loyalty		0.782	0.835	0.860	0.610
BL1	0.786				
BL2	0.881				
BL3	0.845				
BL4	0.577				

4.2.3. Descriptive Statistics and Construct Correlations

For descriptive purposes, composite scores were calculated as the unweighted arithmetic mean of the indicators belonging to each construct, and Pearson correlations among these composite scores are reported in Table 4. All Pearson correlations were positive and statistically significant ($p < 0.001$). The strongest associations were observed between confirmation and satisfaction (r = 0.840) and between satisfaction and continuance intention (r = 0.831), indicating substantial empirical proximity among these post-use constructs. These descriptive composite-score correlations are reported separately from the PLS construct-score correlations used in the discriminant-validity assessment.

Table 4. Descriptive statistics and Pearson correlations among composite scores.

Construct	M	SD	PAIA	CON	SAT	BT	CI	BL
PAIA	3.397	0.776	—					
CON	3.595	0.881	0.618	—				
SAT	3.694	0.826	0.617	0.840	—			
BT	3.373	0.809	0.569	0.688	0.749	—		
CI	3.745	0.880	0.619	0.714	0.831	0.679	—	
BL	3.379	0.815	0.596	0.644	0.722	0.720	0.734	—

Note. M = mean; SD = standard deviation. Correlations are Pearson correlations among unweighted composite scores calculated as the arithmetic mean of each construct's indicators. All off-diagonal correlations are significant at $p < 0.001$. PAIA = perceived AI anthropomorphism; CON = confirmation; SAT = satisfaction; BT = brand trust; CI = continuance intention; BL = brand loyalty; — = diagonal cell (not applicable).

4.2.4. Discriminant Validity

The Fornell–Larcker criterion did not flag a discriminant-validity violation: for each construct, the square root of AVE exceeded its latent-variable correlations with the other constructs (Table 5). The margin was nevertheless narrow for brand loyalty versus continuance intention ($\sqrt{AVE_{BL}}$ = 0.781; $r_{BL,CI}$ = 0.774). Indicator cross-loadings likewise showed that each indicator loaded most strongly on its intended construct. These diagnostics were therefore considered together with the more sensitive HTMT assessment rather than treated as conclusive on their own.

Table 5. Fornell–Larcker criterion.

Construct	PAIA	CON	SAT	BT	CI	BL
PAIA	0.743					
CON	0.624	0.898				
SAT	0.621	0.848	0.906			
BT	0.578	0.704	0.762	0.840		
CI	0.622	0.717	0.830	0.694	0.915	
BL	0.603	0.678	0.760	0.743	0.774	0.781

Note. Diagonal values are the square roots of AVE; off-diagonal values are correlations among the PLS construct scores used in the Fornell–Larcker assessment. These values differ from the unweighted composite-score Pearson correlations reported in Table 4 because PLS construct scores are estimated using indicator weights rather than simple arithmetic means. AVE = average variance extracted. Construct abbreviations as in Table 4.

Standard HTMT values exceeded the stricter 0.85 heuristic for five construct pairs (Table 6): CON–SAT (0.934), SAT–CI (0.907), BT–BL (0.888), CI–BL (0.891), and SAT–BL (0.864). Under the more permissive 0.90 heuristic often used for conceptually similar constructs [45], CON–SAT and SAT–CI remained above the threshold. The 95% bootstrap interval for CON–SAT was [0.905, 0.960], entirely above 0.90; the interval for SAT–CI was [0.872, 0.938]. The intervals for BT–BL and CI–BL crossed 0.90. HTMT2 reproduced the same general pattern, with the highest values for CON–SAT (0.931) and SAT–CI (0.907). As an additional verification, HTMT and HTMT2 were independently recalculated from the 24-indicator correlation matrix following Roemer et al. [46]. All indicator correlations were positive (minimum r = 0.156), satisfying the condition required for HTMT2 computation, and the manually calculated values reproduced the reported values to three decimal places.

AVE exceeded both maximum shared variance (MSV) and average shared variance (ASV) for all constructs: PAIA 0.552/0.389/0.372; BL 0.610/0.599/0.510; BT 0.706/0.581/0.489; SAT 0.820/0.719/0.590; CON 0.807/0.719/0.516; and CI 0.838/0.689/0.534 (AVE/MSV/ASV). However, the BL margin was narrow. Taken together, the Fornell–Larcker and shared-variance diagnostics did not identify a formal violation, whereas HTMT indicates insufficient empirical separation between confirmation and satisfaction and elevated proximity between satisfaction and continuance intention. Rasoolimanesh [50] describes four approaches to assessing discriminant validity in composite-based models: the Fornell–Larcker criterion, cross-loadings, HTMT (evaluated against the 0.85/0.90 thresholds or by testing whether the hypothesis HTMT = 1 can be rejected), and full-collinearity VIFs compared against thresholds of 10, 5, or 3.3. In the present data, the Fornell–Larcker criterion and cross-loadings were satisfied, and all HTMT bootstrap intervals excluded 1 (highest upper bound: 0.960 for CON–SAT). All full-collinearity VIFs (Section 3.4) were below 10; however, satisfaction exceeded 5 (6.13), and confirmation, satisfaction, and continuance intention exceeded 3.3. Some diagnostics met their conventional criteria, but these results do not resolve the substantial construct overlap identified by HTMT and the supplementary CFA assessment (Section 4.2.5). The study therefore does not claim that discriminant validity

is uniformly established, and structural interpretations that depend on partitioning the unique effects of these post-use constructs are made cautiously.

Table 6. HTMT, bootstrap confidence intervals, and HTMT2.

Construct Pair	HTMT	95% Bootstrap CI	HTMT2
PAIA–CON	0.722	[0.643, 0.794]	0.723
PAIA–SAT	0.702	[0.621, 0.772]	0.705
PAIA–BT	0.676	[0.588, 0.752]	0.675
PAIA–CI	0.713	[0.632, 0.787]	0.716
PAIA–BL	0.743	[0.656, 0.821]	0.757
CON–SAT	0.934	[0.905, 0.960]	0.931
CON–BT	0.797	[0.736, 0.848]	0.790
CON–CI	0.801	[0.737, 0.859]	0.800
CON–BL	0.792	[0.728, 0.850]	0.786
SAT–BT	0.844	[0.791, 0.890]	0.839
SAT–CI	0.907	[0.872, 0.938]	0.907
SAT–BL	0.864	[0.811, 0.911]	0.856
BT–CI	0.775	[0.713, 0.830]	0.767
BT–BL	0.888	[0.831, 0.938]	0.893
CI–BL	0.891	[0.842, 0.935]	0.881

Note. HTMT = heterotrait–monotrait ratio of correlations; HTMT2 = HTMT based on geometric means. In the column header, CI denotes confidence interval. Construct abbreviations as in Table 4.

4.2.5. Comparison with Alternative Measurement Structures

Because the EFA did not recover six clean factors, the theory-specified six-factor structure (M6) was compared in confirmatory factor analysis with alternative structures containing fewer factors (Appendix B, Tables A4 and A5). The alternatives merged adjacent constructs (CON + SAT, SAT + CI, BT + BL, and CI + BL), combined CON, SAT, and CI into one factor, specified a three-factor construct-merging alternative informed by the retention results (PAIA; CON + SAT + CI; BT + BL) and a single factor, and specified the dominant item groupings of the four-factor EFA solution with each item loading on one factor only. Under MLR, M6 showed the best relative fit among the models examined (robust CFI = 0.944, robust RMSEA = 0.065, SRMR = 0.044) and the lowest AIC and BIC. Every model that merged factors fit significantly worse according to scaled chi-square difference tests (all $p < 0.001$) [51]; these tests are treated as complementary to the fit indices and information criteria, not as evidence of discriminant validity on their own. The EFA-based groupings came closest but did not fit better than M6 (best alternative: robust CFI = 0.938, robust RMSEA = 0.067, ΔBIC = 18.2). Because these alternatives restrict cross-loadings to zero, they do not reproduce every feature of the exploratory solutions.

This comparison supports the six-factor structure in relative terms only. M6 retained the best relative fit among the models examined under both estimators, although the ordering of the alternative models varied. When the items were treated as ordinal (WLSMV), absolute fit was weaker for every model, including M6 (robust CFI = 0.885, robust RMSEA = 0.109, SRMR = 0.046) [52]. The latent correlations in M6 also remained high (Table A6), particularly for confirmation–satisfaction (MLR: $\varphi = 0.941$, 95% CI [0.915, 0.968]; WLSMV: $\varphi = 0.934$, 95% CI [0.920, 0.949]) and continuance intention–brand loyalty (MLR: $\varphi = 0.910$, 95% CI [0.871, 0.949]). Under the specified CFA model, all confidence intervals excluded a perfect correlation of 1. This does not establish adequate discriminant validity, particularly for the highly correlated pairs: five of the MLR intervals had upper limits above 0.90, a range that Rönkkö and Cho [53] classify as a moderate discriminant-validity problem. The six-factor model is therefore retained because the constructs are theoretically

distinct and no examined alternative represented the data better, not because discriminant validity is regarded as established.

A review of the item content suggests possible contributors to the observed overlap. CON1 ("My experience with ChatGPT met my expectations") and SAT3 ("My experience with ChatGPT has been satisfying") both express an overall evaluation of the experience. SAT4 ("Choosing to use ChatGPT was a wise decision") evaluates the wisdom of the past decision to use the service, whereas continuance intention concerns future use; its exploratory loading with the continuance-intention items suggests imperfect empirical separation in this sample. Two continuance-intention items (CI1 and CI2) also refer to "the ChatGPT brand", as do the brand-loyalty items that express preference (BL1 and BL3), which may contribute to the overlap between these two constructs. No items were removed, because removing items on the basis of the same data would adapt the measurement model to this sample. Instead, the overlap is taken into account in interpreting the structural results, and a sensitivity model in which confirmation and satisfaction are combined is reported in Appendix C.

4.3. Structural Model

The structural model was evaluated using 5000 bootstrap subsamples (Table 7 and Figure 2). Inner-model VIF values ranged from 1.000 to 4.399 and remained below the commonly applied threshold of 5 [37], indicating no critical predictor-collinearity problem under that criterion. PAIA was positively associated with confirmation ($\beta = 0.624$, $p < 0.001$), satisfaction ($\beta = 0.081$, $p = 0.006$), and brand trust ($\beta = 0.578$, $p < 0.001$). Brand trust was positively associated with satisfaction ($\beta = 0.306$, $p < 0.001$), continuance intention ($\beta = 0.144$, $p < 0.001$), and brand loyalty ($\beta = 0.333$, $p < 0.001$). Confirmation was positively associated with satisfaction ($\beta = 0.581$, $p < 0.001$), but its direct association with continuance intention was not significant ($\beta = 0.018$, $p = 0.763$). Satisfaction was positively associated with continuance intention ($\beta = 0.705$, $p < 0.001$) and brand loyalty ($\beta = 0.179$, $p = 0.003$), and continuance intention was positively associated with brand loyalty ($\beta = 0.394$, $p < 0.001$). Thus, 10 of the 11 proposed hypotheses were supported.

Table 7. Structural relationships, bootstrap standard errors, predictor VIF values, and hypothesis decisions.

Hypothesis	Relationship	β	SE	*t*	*p*	VIF	Decision
H1	PAIA → CON	0.624	0.036	17.186	<0.001	1.000	Supported
H2	PAIA → SAT	0.081	0.030	2.726	0.006	1.747	Supported
H3	PAIA → BT	0.578	0.038	15.165	<0.001	1.000	Supported
H4	BT → SAT	0.306	0.038	7.999	<0.001	2.117	Supported
H5	BT → CI	0.144	0.041	3.532	<0.001	2.459	Supported
H6	BT → BL	0.333	0.043	7.702	<0.001	2.460	Supported
H7	CON → SAT	0.581	0.039	14.790	<0.001	2.309	Supported
H8	CON → CI	0.018	0.061	0.301	0.763	3.656	Not supported
H9	SAT → CI	0.705	0.056	12.587	<0.001	4.399	Supported
H10	SAT → BL	0.179	0.061	2.940	0.003	4.099	Supported
H11	CI → BL	0.394	0.058	6.835	<0.001	3.314	Supported

Note. SE = bootstrap standard error (STDEV); 5000 bootstrap subsamples. β = standardized path coefficient; *t* = t-value; *p* = *p*-value; VIF = variance inflation factor. Construct abbreviations as in Table 4.

The PAIA–satisfaction coefficient was small ($\beta = 0.081$, SE = 0.030) but statistically significant ($t = 2.726$, $p = 0.006$). The small bootstrap standard error is consistent with the relatively large sample ($N = 555$) and the high explained variance of satisfaction ($R^2 = 0.776$). As Kock and Dow [49] note, small coefficients can reach statistical significance in large

samples; this path is therefore interpreted together with its effect size ($f^2 = 0.017$), which indicates a statistically detectable but practically negligible association.

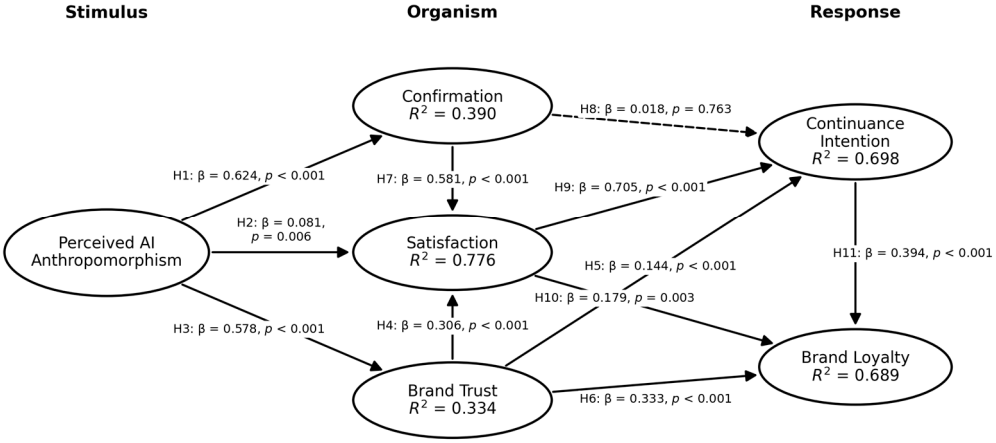


Figure 2. Estimated structural model. Solid arrows indicate statistically significant paths; the dashed H8 path was not statistically significant. Values in endogenous constructs are R^2.

SmartPLS fit indices were reported as supplementary diagnostics rather than as the primary basis for model evaluation. Saturated-model SRMR was 0.062 and NFI was 0.850; estimated-model SRMR was 0.103 and NFI was 0.843 (Table 8). The higher estimated-model SRMR reflects the additional structural restrictions relative to the saturated model; accordingly, these indices are reported descriptively and are not used to claim good global fit.

Table 8. SmartPLS model-fit diagnostics.

Model	SRMR	d_ULS	d_G	χ^2	NFI
Saturated	0.062	1.136	0.479	1559.445	0.850
Estimated	0.103	3.152	0.594	1625.976	0.843

Note. SRMR = standardized root mean square residual; d_ULS = squared Euclidean distance; d_G = geodesic distance; χ^2 = chi-square statistic; NFI = normed fit index.

4.4. Explanatory Power, Predictive Assessment, and Effect Sizes

The model explained 39.0% of the variance in confirmation, 33.4% in brand trust, 77.6% in satisfaction, 69.8% in continuance intention, and 68.9% in brand loyalty (Table 9). Adjusted R^2 values were 0.389, 0.333, 0.775, 0.697, and 0.687, respectively.

Table 9. Explained variance of endogenous constructs.

Endogenous Construct	R^2	Adjusted R^2
Confirmation	0.390	0.389
Brand trust	0.334	0.333
Satisfaction	0.776	0.775
Continuance intention	0.698	0.697
Brand loyalty	0.689	0.687

Out-of-sample predictive performance was evaluated with PLSpredict using 10 folds and 10 repetitions. All endogenous indicators yielded positive Q^2_predict values, ranging from 0.123 to 0.333 (Table 10). Prediction-error skewness ranged from −0.783 to 0.142, so RMSE was used as the primary error metric. Compared with the linear-model benchmark, PLS-SEM produced lower RMSE for 11 of the 18 endogenous indicators, equal RMSE for three, and higher RMSE for four. Following Shmueli et al. [47], this pattern is consistent

with medium predictive power, although the advantage was uneven across indicators and error metrics. Three of the four brand-loyalty indicators had higher RMSE than the linear benchmark, and BL4 had the lowest Q^2_predict (0.123). The MAE comparison was less favorable overall.

Table 10. PLSpredict results (10 folds, 10 repetitions).

Indicator	Q^2_Predict	PLS RMSE	LM RMSE	PLS MAE	LM MAE
BL1	0.199	0.950	0.955	0.702	0.698
BL2	0.308	0.769	0.767	0.566	0.567
BL3	0.220	0.902	0.901	0.708	0.692
BL4	0.123	1.145	1.118	0.969	0.923
BT1	0.252	0.828	0.830	0.641	0.635
BT2	0.124	0.989	0.974	0.775	0.769
BT3	0.235	0.832	0.840	0.656	0.658
BT4	0.300	0.745	0.750	0.567	0.565
SAT1	0.319	0.748	0.748	0.564	0.551
SAT2	0.329	0.732	0.736	0.548	0.543
SAT3	0.333	0.738	0.744	0.560	0.563
SAT4	0.265	0.816	0.821	0.616	0.613
CON1	0.324	0.756	0.756	0.574	0.569
CON2	0.287	0.881	0.885	0.668	0.673
CON3	0.319	0.809	0.811	0.601	0.601
CI1	0.330	0.807	0.807	0.604	0.597
CI2	0.307	0.765	0.767	0.569	0.569
CI3	0.305	0.818	0.819	0.607	0.601

Note. Q^2_predict = PLSpredict Q^2; RMSE = root mean squared error; MAE = mean absolute error; PLS = partial least squares path model; LM = linear regression model benchmark. Indicator codes are defined in Table A1.

Effect sizes were interpreted using Cohen's [54] conventional benchmarks (Table 11). PAIA had large effects on confirmation (f^2 = 0.639) and brand trust (f^2 = 0.502), confirmation had a large effect on satisfaction (f^2 = 0.654), and satisfaction had a large effect on continuance intention (f^2 = 0.374). Brand trust had a medium effect on satisfaction (f^2 = 0.198), while its effects on continuance intention (f^2 = 0.028) and brand loyalty (f^2 = 0.145) were small. Continuance intention had a medium effect on brand loyalty (f^2 = 0.151). The direct PAIA–satisfaction effect was negligible (f^2 = 0.017), confirmation had no observable direct effect on continuance intention (f^2 = 0.000), and the satisfaction–brand-loyalty effect was small (f^2 = 0.025).

Table 11. Effect sizes.

Relationship	f^2	Interpretation
PAIA → CON	0.639	Large
PAIA → BT	0.502	Large
PAIA → SAT	0.017	Negligible
CON → SAT	0.654	Large
CON → CI	0.000	No effect
BT → SAT	0.198	Medium
BT → CI	0.028	Small
BT → BL	0.145	Small
SAT → CI	0.374	Large
SAT → BL	0.025	Small
CI → BL	0.151	Medium

Note. f^2 = effect size. Construct abbreviations as in Table 4.

4.5. Specific Indirect Effects

Confirmation had a significant specific indirect association with continuance intention through satisfaction (β = 0.410, $p < 0.001$), whereas its direct association with continuance intention was not significant (Table 12). Given the empirical proximity between confirmation and satisfaction, this pattern is reported descriptively rather than labelled as definitive indirect-only mediation [55]. Confirmation also had a significant indirect association with brand loyalty through satisfaction (β = 0.104, $p = 0.004$). Because a direct confirmation–brand-loyalty path was not specified, this result is reported as a specific indirect association rather than as a mediation classification.

Table 12. Selected specific indirect effects.

Indirect Path	β	*p*	Interpretation
CON → SAT → CI	0.410	<0.001	Significant specific indirect effect
CON → SAT → BL	0.104	0.004	Significant specific indirect effect
PAIA → CON → SAT	0.363	<0.001	Significant specific indirect effect
PAIA → BT → SAT	0.177	<0.001	Significant specific indirect effect
SAT → CI → BL	0.278	<0.001	Significant specific indirect effect
PAIA → BT → BL	0.193	<0.001	Significant specific indirect effect
PAIA → CON → SAT → CI	0.256	<0.001	Significant serial indirect effect
CON → SAT → CI → BL	0.162	<0.001	Significant serial indirect effect

Note. β = standardized indirect effect; *p* = *p*-value. Construct abbreviations as in Table 4.

PAIA had significant specific indirect associations with satisfaction through confirmation (β = 0.363, $p < 0.001$) and through brand trust (β = 0.177, $p < 0.001$). Its direct association with satisfaction remained statistically significant but small (β = 0.081; $f^2 = 0.017$). Because confirmation and satisfaction are empirically close, these findings are interpreted as a pattern consistent with upstream appraisal rather than as proof of a causal mechanism. Satisfaction was indirectly associated with brand loyalty through continuance intention (β = 0.278, $p < 0.001$), and PAIA had a positive indirect association with brand loyalty through brand trust (β = 0.193, $p < 0.001$). Two longer indirect associations were also significant: PAIA → CON → SAT → CI (β = 0.256, $p < 0.001$) and CON → SAT → CI → BL (β = 0.162, $p < 0.001$).

5. Discussion

This study examined how users' perceptions of humanlike characteristics in ChatGPT are associated with post-use evaluations, continuance intention, and loyalty toward ChatGPT as a branded generative AI service. The findings show a differentiated pattern: PAIA had large relationships with confirmation and brand trust, whereas its direct relationship with satisfaction was statistically significant but practically negligible. Confirmation and brand trust were each associated with satisfaction, satisfaction was strongly associated with continuance intention, and brand trust, satisfaction, and continuance intention were associated with brand loyalty.

Within the specified cross-sectional model, this pattern is more consistent with an upstream-appraisal account than with a simple direct-effect account. Humanlike perceptions covaried more strongly with users' judgments that the service had met expectations and with confidence in the brand than with satisfaction after the other predictors were included. Because confirmation and satisfaction were empirically close, this interpretation depends partly on separating the two constructs. A sensitivity model combining them (Appendix C) showed a substantial association between PAIA and post-use evaluation and similar magnitudes for the BT → CI, BT → BL, and CI → BL paths, but it cannot independently substantiate the interpretation involving confirmation and satisfaction as

separate constructs. The upstream-appraisal interpretation is therefore offered as tentative rather than as a definitive causal sequence.

5.1. Perceived AI Anthropomorphism and Post-Use Evaluation

The strong relationships of PAIA with confirmation and brand trust are consistent with the view that users draw on humanlike cues when interpreting both the performance and relational meaning of conversational AI. Participants who perceived ChatGPT as displaying personality, recognition, personalization, and humanlike communication were more likely to report that the service had met their expectations and to express confidence in the ChatGPT brand.

The relationship between anthropomorphism and brand trust is consistent with prior evidence that humanlike perceptions can extend beyond an interface and become associated with evaluations of the brand represented by that interface. Patrizi et al. [3], for example, found that brand anthropomorphism in voice-based AI was positively related to brand trust and consumer–brand engagement. The present findings show a comparable association in the context of generative AI.

The results also complement Hussain's [4] work on generative-AI brand anthropomorphism. Hussain examined how anthropomorphic attributes were associated with brand respect and brand heroism, whereas the present study focuses on how interaction-level PAIA is associated with confirmation and brand trust and how these evaluations relate to satisfaction, continuance intention, and brand loyalty. This distinction separates the perception measured during interaction from downstream evaluations directed toward the branded service.

The direct relationship between PAIA and satisfaction requires a more nuanced interpretation. Although statistically significant, its coefficient was small and its effect size was negligible. This resembles Rita et al. [8], who found that information quality, problem-solving capability, and understanding humanness predicted satisfaction with service chatbots, whereas several general anthropomorphic cues did not. The present model suggests that a limited direct association with satisfaction can coexist with stronger associations of PAIA with confirmation and brand trust. The significant indirect associations through these constructs are consistent with an upstream-appraisal interpretation, but the cross-sectional design and the empirical proximity between confirmation and satisfaction preclude a strong causal claim. Because the combined-construct sensitivity model in Appendix C does not estimate confirmation and satisfaction separately, it cannot independently corroborate this confirmation-specific interpretation.

This interpretation is also compatible with Pham et al. [11], who linked trust in ChatGPT with satisfaction and satisfaction with continuance intention. Together, these comparisons suggest that anthropomorphic perceptions may be most informative when studied alongside performance-based and relational appraisals rather than as an isolated direct source of satisfaction.

5.2. The Role of Confirmation and Satisfaction in Continued Use

The strong relationship between confirmation and satisfaction is consistent with the central logic of the Expectation-Confirmation Model. Participants who believed that ChatGPT had met or exceeded their initial expectations also reported greater satisfaction. Confirmation had a large f^2 effect on satisfaction, underscoring the importance of the comparison between expected and experienced performance within the estimated model.

This result is consistent with Chau et al. [10], who integrated expectation-confirmation logic with UTAUT in AI-powered customer service and found that fulfilled expectations and delivered value were closely related to satisfaction and subsequent continued use.

The present study differs by focusing on a single branded generative-AI service and by positioning PAIA as an antecedent associated with the confirmation process while extending the outcomes to brand loyalty.

The direct confirmation–continuance-intention relationship was not significant once satisfaction was included, whereas the specific indirect association CON → SAT → CI was significant. This pattern is compatible with the original ECM emphasis on satisfaction as a key post-use evaluation linking confirmation with continued use. It should not, however, be treated as definitive evidence of indirect-only mediation because confirmation and satisfaction showed substantial empirical proximity in the present data. Their shared variance may reduce the unique structural contribution attributed to confirmation when both are entered simultaneously. The confirmatory comparisons in Section 4.2.5 point in the same direction: the latent correlation between the two constructs was 0.94, and a review of the item content suggests that some of their items share evaluative content.

The result differs from Li et al. [29], who reported a positive direct confirmation–continuance relationship in social fitness-tracking applications. The contrast may reflect differences in service context, task scope, and model specification. Future studies using longitudinal designs and refined measurement could determine whether confirmation has an independent prospective association with continuance in generative-AI settings.

5.3. Brand Trust as a Relational Mechanism

Brand trust formed a distinct relational pattern in the model. Users who perceived ChatGPT as more humanlike also reported greater confidence in the reliability, data handling, honesty, and performance of the ChatGPT brand. Brand trust was in turn associated with satisfaction, continuance intention, and brand loyalty.

This pattern is consistent with research showing that anthropomorphic perceptions can be associated with trust in AI-mediated brand relationships. Patrizi et al. [3] identified brand trust as an important consequence of anthropomorphism in voice-based AI, while Shahzad et al. [12] linked chatbot user trust with e-brand loyalty. The present model connects these relational evaluations with both post-use experience and brand-level outcomes in a generative-AI context.

Brand trust was positively associated with continuance intention, although its coefficient was smaller than the satisfaction–continuance coefficient. Brand trust was also positively associated with brand loyalty, and its direct coefficient was numerically larger than the direct satisfaction–loyalty coefficient. Because the study did not formally test the difference between these coefficients, the comparison is descriptive only.

5.4. Satisfaction, Continuance Intention, and Brand Loyalty

Satisfaction had the strongest structural relationship with continuance intention, consistent with established post-adoption research and with recent AI-service studies. Rita et al. [8] similarly reported a strong relationship between satisfaction and loyalty to chatbot usage, while Chau et al. [10] linked satisfaction with continued engagement in AI-powered customer service.

The present study separates continuance intention from brand loyalty. Continuance intention represents a prospective plan to keep using ChatGPT, whereas brand loyalty captures first preference, recommendation, preference over comparable alternatives, and an attachment component. Users may continue using a service because it is familiar, useful, accessible, or integrated into routine activities without necessarily preferring its brand over competitors. The two constructs are conceptually distinct in the model, although they showed substantial empirical overlap and their empirical separation could not be

adequately demonstrated (HTMT = 0.891; 95% bootstrap interval [0.842, 0.935], crossing 0.90; CFA latent correlation = 0.910, Table A6).

Satisfaction was associated with brand loyalty both directly and indirectly through continuance intention. These results are consistent with the view that favorable post-use evaluation and future-use intention are related to, but do not exhaust, brand loyalty. The separate modeling of continuance intention and brand loyalty thus broadens post-adoption analysis from continued system use to a relational outcome directed toward the branded service.

5.5. Theoretical Contributions

The study offers four focused theoretical contributions. First, it distinguishes interaction-level PAIA from brand-level trust and loyalty, aligning the construct label with the administered anthropomorphism items rather than treating humanlike communication as anthropomorphism of the brand itself. Second, it uses S-O-R as an overarching structure that links anthropomorphism/CASA, expectation-confirmation logic, and consumer–brand relationship research within a single post-use model.

Third, the study frames the role of PAIA as a comparison between a direct-effect account and an upstream-appraisal account. The observed pattern—large PAIA relationships with confirmation and brand trust but a very small direct relationship with satisfaction—is more consistent with the latter within the specified model. This contribution is intentionally framed as evidence about relative associations rather than as proof of a causal mechanism, because the design is cross-sectional and confirmation and satisfaction are empirically close. Because this contrast relies on measuring confirmation and satisfaction as separate constructs, which overlapped substantially in the present data, it should be retested with measures designed to separate them more clearly.

Fourth, the model maintains a conceptual distinction between continuance intention and brand loyalty while acknowledging substantial empirical overlap between them in this sample. Continued use of a generative-AI service and loyalty toward its brand are therefore modeled as related but distinct outcomes that future research with refined measures should test more stringently. In this way, the model connects human–AI interaction with both post-adoption technology use and consumer–brand relationship research.

5.6. Practical Implications

For managers of generative-AI services, the findings suggest that humanlike interaction should be supported by dependable performance and credible brand conduct rather than treated as a stand-alone route to satisfaction. The small direct PAIA–satisfaction coefficient indicates that making an interface feel more human is unlikely to compensate for unmet expectations or weak trust.

Expectation management is therefore important. Marketing messages, onboarding materials, and in-product guidance should communicate capabilities realistically, identify situations in which outputs may be uncertain, and indicate when information should be independently verified. The strong confirmation–satisfaction association suggests that consistency between what users expect and what the service delivers is closely related to favorable post-use evaluation.

Brand trust likewise requires visible reliability and transparent conduct. Providers should explain how user data are handled, acknowledge errors and limitations, and avoid socially confident responses when the system cannot provide dependable information. Retention and brand loyalty should also be monitored as different outcomes: a user may intend to continue using an AI service without preferring its brand over comparable alternatives.

5.7. Limitations and Future Research

Several limitations relate to the design of the study and indicate directions for future research. First, the cross-sectional, single-source design does not establish temporal order or causality, and all constructs were measured through self-reports at one point in time; the diagnostics reported in Section 3.4 cannot separate substantive covariance from method variance. Time-lagged or multi-source designs, experimental manipulation of specific anthropomorphic cues, and behavioral usage data would allow the proposed associations to be examined more rigorously.

Second, the items for the adjacent post-use constructs were not designed to maximize their empirical separation. The measurement assessment (Sections 4.2.4 and 4.2.5) indicated substantial overlap between some of these constructs. Future studies should use items that separate the comparison with prior expectations from the overall evaluation of the service more sharply, for example by anchoring confirmation items explicitly to what users expected before use, and should test the confirmation–satisfaction distinction with measures validated in an independent sample.

Third, the Turkish translation was evaluated through expert review rather than a formal back-translation procedure, and no separate pilot study was conducted. Although expert review supported clarity and contextual appropriateness, future work should use formal translation-equivalence procedures and independent pretesting.

Fourth, the study used convenience sampling and focused on ChatGPT users in Türkiye. ChatGPT is an analytically important branded generative-AI service, but it is not a statistically representative proxy for all generative-AI systems. Replication across other brands, countries, task domains, levels of AI familiarity, and paid versus free usage settings is needed.

Fifth, PAIA was modeled as a single reflective construct even though EFA suggested internal differentiation between humanlike communication/behavior and familiarity/personalization indicators. Future studies could examine whether these facets have distinct effects and could manipulate specific cues experimentally. The comparatively low BL4 loading also indicates that the attachment component of brand loyalty warrants further scale refinement. The sensitivity analysis in Appendix C showed that removing BL4 did not alter the direction or statistical significance of the structural paths, but independent scale validation would strengthen future work.

Finally, the study focused on continuance intention and general brand loyalty. Future research could examine subscription intention, willingness to pay, resistance to switching, brand advocacy, forgiveness after service failure, and reactions to AI errors. Such outcomes may help clarify when favorable experience develops into economically and relationally consequential behavior.

6. Conclusions

This study examined how perceived humanlike characteristics during interaction with ChatGPT are associated with post-use evaluations, continuance intention, and loyalty toward a branded generative-AI service. Using survey data from 555 ChatGPT users in Türkiye, the study integrated PAIA into an S-O-R structure combining expectation-confirmation and consumer–brand relationship perspectives.

The findings show a pattern in which PAIA is much more strongly associated with confirmation and brand trust than with satisfaction after the other predictors are included. Confirmation and brand trust are each associated with satisfaction, satisfaction is strongly associated with continuance intention, and brand trust, satisfaction, and continuance intention are associated with brand loyalty. This pattern is more consistent with an upstream-appraisal interpretation than with a simple direct-effect account, but the substantial empiri-

cal proximity between confirmation and satisfaction—and the elevated proximity between satisfaction and continuance intention—requires caution when interpreting unique structural effects. The combined-construct sensitivity model showed a substantial association between PAIA and post-use evaluation and similar magnitudes for the BT → CI, BT → BL, and CI → BL paths, but it cannot independently substantiate the interpretation involving confirmation and satisfaction as separate constructs; that interpretation remains tentative.

The study also maintains a conceptual distinction between continued use and loyalty toward an AI brand, while acknowledging substantial empirical overlap between the two constructs. Humanlike interaction alone does not account for favorable brand-related outcomes; its relevance appears to depend on how it is associated with fulfilled expectations and confidence in the branded service. Because the evidence is cross-sectional, these conclusions concern patterns of association rather than verified causal processes.

Author Contributions: G.E. conceptualized the study, developed the theoretical framework, structured the methodology, and wrote the original manuscript. E.G. contributed to the literature review, data curation, statistical analysis, and supervision. M.F.C. provided academic supervision, validated the research design, and critically revised the manuscript for important intellectual content. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding. The APC was funded by the Fırat University Scientific Research Projects Coordination Unit (FÜBAP) under Project No. İİBF.26.09.

Institutional Review Board Statement: Ethical approval for the study was granted by the Fırat University Social and Human Sciences Research Ethics Committee on 30 October 2025 (Meeting No. 2025/23, Decision No. 33). Participation was voluntary, and informed consent was obtained before respondents proceeded to the questionnaire. No personally identifying information was collected.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Acknowledgments: This article is based on the master's thesis of the first author, Gamze Eren, entitled "Yapay Zekâ Marka Antropomorfizmi Bağlamında Marka Güveni, Onay, Memnuniyet ve Sürekli Kullanım Niyetinin Marka Sadakati Üzerindeki Rolü: ChatGPT Örneği" [The Role of Brand Trust, Confirmation, Satisfaction, and Continuance Intention in Brand Loyalty in the Context of AI Brand Anthropomorphism: The Case of ChatGPT], completed in 2026 at the Department of Business Administration, Institute of Social Sciences, Fırat University (YÖK National Thesis Center, Thesis No. 1013966). The conceptual framing and analyses were further developed for the present article. During the preparation of this manuscript, the authors used ChatGPT (OpenAI; https://chatgpt.com) and Claude (Anthropic; https://claude.ai), web-based services accessed in 2026, in a supporting role for language editing and technical assistance with the supplementary statistical analyses. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Measurement Items

Table A1. Measurement items administered in Turkish, corresponding English wording, and source/provenance information.

Construct	Code	English Item	Turkish Item	Source/Provenance
Perceived AI anthropomorphism	AIBA1	ChatGPT exhibits human-like characteristics.	ChatGPT insan benzeri özellikler sergiler.	Adapted from Noor et al. [34]

Table A1. *Cont.*

Construct	Code	English Item	Turkish Item	Source/Provenance
Perceived AI anthropomorphism	AIBA2	ChatGPT has a unique personality.	ChatGPT'nin kendine özgü bir kişiliği vardır.	Adapted from Noor et al. [34]
Perceived AI anthropomorphism	AIBA3	As I continue interacting with ChatGPT, it gets to know me better.	ChatGPT ile etkileşim kurdukça beni daha iyi tanıyor.	Adapted from Noor et al. [34]
Perceived AI anthropomorphism	AIBA4	ChatGPT responds in ways that resemble human behavior.	ChatGPT, insan davranışlarını andıran tepkiler verir.	Adapted from Noor et al. [34]
Perceived AI anthropomorphism	AIBA5	ChatGPT provides personalized responses based on users' characteristics.	ChatGPT, kullanıcı özelliklerine göre kişiselleştirilmiş yanıtlar verir.	Adapted from Noor et al. [34]
Perceived AI anthropomorphism	AIBA6	ChatGPT communicates in a human-like manner.	ChatGPT, insan benzeri bir iletişim tarzına sahiptir.	Adapted from Noor et al. [34]
Brand trust	BT1	I believe that the ChatGPT brand provides accurate and reliable responses.	ChatGPT markasının yanıtlarının doğru ve güvenilir olduğunu düşünüyorum.	Contextually adapted from brand-trust literature; see Delgado-Ballester [18] and Ghorbanzadeh et al. [23]
Brand trust	BT2	I believe that the ChatGPT brand handles my data ethically and securely.	ChatGPT markasının verilerimi etik ve güvenli bir şekilde işlediğini düşünüyorum.	Contextually adapted from brand-trust literature; see Delgado-Ballester [18] and Ghorbanzadeh et al. [23]
Brand trust	BT3	The ChatGPT brand is honest and sincere in its interactions and acknowledges its errors or limitations.	ChatGPT markası, etkileşimlerinde dürüst ve samimidir; hatalarını veya sınırlılıklarını kabul eder.	Contextually adapted from brand-trust literature; see Delgado-Ballester [18] and Ghorbanzadeh et al. [23]
Brand trust	BT4	I trust the performance of the ChatGPT brand.	ChatGPT markasının performansına güveniyorum.	Contextually adapted from brand-trust literature; see Delgado-Ballester [18] and Ghorbanzadeh et al. [23]
Confirmation	CON1	My experience with ChatGPT met my expectations.	ChatGPT kullanma deneyimim beklentilerimi karşıladı.	Contextualized from Bhattacherjee [9]
Confirmation	CON2	ChatGPT's performance exceeded my initial expectations.	ChatGPT'nin performansı, başlangıçtaki beklentilerimi aştı.	Contextualized from Bhattacherjee [9]
Confirmation	CON3	Overall, ChatGPT met my expectations to a great extent.	Genel olarak ChatGPT beklentilerimi büyük ölçüde karşıladı.	Contextualized from Bhattacherjee [9]
Satisfaction	SAT1	Overall, I am satisfied with ChatGPT.	Genel olarak ChatGPT uygulamasından memnunum.	Contextualized for the present study based on the ECM satisfaction construct [9]
Satisfaction	SAT2	I am satisfied with the services provided by ChatGPT.	ChatGPT'nin sunduğu hizmetlerden memnunum.	Contextualized for the present study based on the ECM satisfaction construct [9]
Satisfaction	SAT3	My experience with ChatGPT has been satisfying.	ChatGPT ile yaşadığım deneyimler tatmin edicidir.	Contextualized for the present study based on the ECM satisfaction construct [9]

Table A1. *Cont.*

Construct	Code	English Item	Turkish Item	Source/Provenance
Satisfaction	SAT4	Choosing to use ChatGPT was a wise decision.	ChatGPT'yi kullanma kararımın akıllıca olduğunu düşünüyorum.	Adapted from Noor et al. [34]
Continuance intention	CI1	I intend to continue using the ChatGPT brand in the future.	ChatGPT markasını gelecekte kullanmaya devam etmeyi düşünüyorum.	Contextualized from Bhattacherjee [9]
Continuance intention	CI2	I would choose the ChatGPT brand again when I have similar needs.	Benzer ihtiyaçlarımda yine ChatGPT markasını kullanmayı düşünürüm.	Contextualized from Bhattacherjee [9]
Continuance intention	CI3	I plan to continue using ChatGPT in my daily tasks and academic work.	ChatGPT'yi günlük işlerimde/akademik çalışmalarımda kullanmayı sürdürmeyi planlıyorum.	Contextualized from Bhattacherjee [9]
Brand loyalty	BL1	ChatGPT is my first-choice artificial intelligence application.	ChatGPT markası, tercih ettiğim ilk yapay zekâ uygulamasıdır.	Contextually adapted from Yoo and Donthu [36] and Cheng and Jiang [35]
Brand loyalty	BL2	I would recommend the ChatGPT brand to others.	ChatGPT markasını başkalarına tavsiye ederim.	Contextually adapted from Yoo and Donthu [36] and Cheng and Jiang [35]
Brand loyalty	BL3	Even if AI assistants from other brands offer similar features, I would still prefer the ChatGPT brand.	Diğer markaların yapay zekâ asistanları benzer özellikler sunsa bile ChatGPT markasını tercih ederim.	Contextually adapted from Yoo and Donthu [36] and Cheng and Jiang [35]
Brand loyalty	BL4	I feel emotionally attached to the ChatGPT brand.	ChatGPT markasına duygusal olarak bağlılık hissediyorum.	Study-specific item capturing the attachment component of brand loyalty

Note. AIBA = perceived AI anthropomorphism items; CON = confirmation; SAT = satisfaction; BT = brand trust; CI = continuance intention; BL = brand loyalty.

Appendix B. Exploratory and Confirmatory Factor Analyses

Table A2 reports the three-factor principal-axis solution with Promax rotation. Coefficients with absolute values below 0.30 are suppressed. Table A3 reports the forced six-factor solution using the same extraction and rotation method.

Table A2. Three-factor PAF/Promax pattern matrix.

Indicator	F1	F2	F3
SAT1	0.967		
SAT2	0.954		
SAT4	0.821		
CON3	0.807		
CON1	0.805		
CI3	0.783		
CI1	0.781		
BL2	0.753		
SAT3	0.738		
CI2	0.701		
CON2	0.636		
BT4	0.540		
BL1	0.513		

Table A2. *Cont.*

Indicator	F1	F2	F3
AIBA4		0.745	
AIBA6		0.655	
AIBA1		0.624	
AIBA3	0.308	0.580	
AIBA5	0.352	0.561	
BT2			0.739
BL4			0.586
BL3	0.327		0.491
BT1	0.425		0.475
AIBA2		0.409	0.471
BT3	0.355		0.418

Note. PAF = principal axis factoring; F1–F3 = extracted factors. Coefficients with absolute values < 0.30 are suppressed. Indicator codes are defined in Table A1.

Table A3. Forced six-factor PAF/Promax pattern matrix.

Indicator	F1	F2	F3	F4	F5	F6
CON1	0.916					
CON3	0.914					
CON2	0.802					
SAT1	0.787					
SAT2	0.772					
SAT3	0.666					
BT2		0.988				
BT3		0.581				
BT1		0.501				
BL4		0.460				
BT4		0.426				
BL3		0.327				
CI1			0.870			
CI2			0.821			
CI3			0.758			
SAT4			0.570			
AIBA4				0.736		
AIBA1				0.685		
AIBA6				0.596		
AIBA2				0.558		
AIBA5					0.848	
AIBA3					0.498	
BL1						0.758
BL2						0.437

Note. Coefficients with absolute values < 0.30 are suppressed. The exploratory solutions were used diagnostically and did not determine the theory-specified PLS-SEM measurement model. PAF = principal axis factoring; F1–F6 = extracted factors. Indicator codes are defined in Table A1.

Tables A4–A6 report the confirmatory comparisons described in Section 4.2.5. All models were estimated in R with lavaan 0.6-17, with latent variances fixed to 1. All solutions converged and were admissible.

Table A4. Confirmatory comparison of alternative measurement structures (MLR).

Model	Structure	χ^2 (df)	CFI	RMSEA	SRMR	BIC	$\Delta\chi^2$ (Δdf)
M6	Six constructs (theory)	613.26 (237)	0.944	0.065	0.044	28,455.9	—
M5a	CON + SAT	670.03 (242)	0.936	0.069	0.046	28,509.7	53.94 (5)
M5b	SAT + CI	760.13 (242)	0.922	0.076	0.046	28,654.3	100.57 (5)
M5c	BT + BL	695.50 (242)	0.932	0.071	0.045	28,553.3	64.79 (5)
M5d	CI + BL	670.42 (242)	0.936	0.069	0.046	28,511.5	52.26 (5)
M4a	CON + SAT + CI	836.17 (246)	0.911	0.081	0.048	28,745.9	170.14 (9)
M4b	CON + SAT; CI + BL	727.11 (246)	0.928	0.072	0.048	28,571.4	106.03 (9)
M4c	EFA groupings; BL3 with CI	678.76 (246)	0.935	0.069	0.046	28,499.8	—
M4d	EFA groupings; BL3 with BT	660.82 (246)	0.938	0.067	0.045	28,474.1	—
M3	PAIA; CON + SAT + CI; BT + BL	893.99 (249)	0.902	0.084	0.049	28,820.7	213.34 (12)
M1	Single factor	1297.36 (252)	0.841	0.107	0.066	29,424.0	497.62 (15)

Note. χ^2 = scaled test statistic; CFI and RMSEA are robust indices. $\Delta\chi^2$ = Satorra–Bentler scaled chi-square difference test against M6, reported for the nested models that merge factors (all $p < 0.001$). M4c and M4d specify the dominant item groupings of the four-factor EFA solution without cross-loadings (CON1–CON3 and SAT1–SAT3; BT1–BT4 and BL4; CI1–CI3, SAT4, BL1, and BL2; PAIA; BL3 assigned as indicated); they are not nested in M6 and are compared using BIC. AIC was also lowest for M6 (28,183.8). MLR = robust maximum likelihood; CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion; EFA = exploratory factor analysis; — = not applicable (reference model or non-nested model). Construct abbreviations as in Table 4.

Table A5. Sensitivity of the model comparison to ordinal estimation (WLSMV).

Model	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$ (Δdf)
M6	0.885	0.866	0.109	0.046	—
M5a	0.874	0.857	0.113	0.047	133.65 (5)
M5b	0.852	0.831	0.122	0.049	256.59 (5)
M5c	0.870	0.852	0.114	0.048	146.17 (5)
M5d	0.874	0.856	0.113	0.048	113.62 (5)
M4a	0.840	0.821	0.126	0.052	376.55 (9)
M4b	0.863	0.846	0.117	0.050	235.69 (9)
M4c	0.870	0.855	0.113	0.048	—
M4d	0.873	0.858	0.112	0.047	—
M3	0.827	0.809	0.130	0.053	463.65 (12)
M1	0.759	0.736	0.153	0.075	986.28 (15)

Note. All items declared ordinal. CFI, TLI, and RMSEA are the robust indices reported by lavaan [52]. $\Delta\chi^2$ = scaled chi-square difference test against M6 for nested models (all $p < 0.001$). Information criteria are not available for WLSMV. Model labels as in Table A4. WLSMV = weighted least squares mean- and variance-adjusted estimation; TLI = Tucker–Lewis index; — = not applicable. Other abbreviations as in Table A4.

Table A6. Latent correlations in the six-factor model (M6).

Construct Pair	MLR φ [95% CI]	WLSMV φ [95% CI]
CON–SAT	0.941 [0.915, 0.968]	0.934 [0.920, 0.949]
CI–BL	0.910 [0.871, 0.949]	0.884 [0.862, 0.906]
SAT–CI	0.892 [0.852, 0.932]	0.892 [0.874, 0.910]
SAT–BL	0.873 [0.827, 0.919]	0.854 [0.829, 0.878]
BT–BL	0.868 [0.819, 0.917]	0.869 [0.843, 0.896]
SAT–BT	0.842 [0.792, 0.892]	0.838 [0.811, 0.865]
CON–BT	0.815 [0.762, 0.869]	0.795 [0.760, 0.829]
CON–CI	0.806 [0.747, 0.865]	0.802 [0.768, 0.836]
CON–BL	0.803 [0.750, 0.857]	0.790 [0.755, 0.825]
CI–BT	0.795 [0.741, 0.849]	0.785 [0.753, 0.818]
PAIA–CON	0.718 [0.638, 0.798]	0.715 [0.666, 0.764]
PAIA–CI	0.707 [0.626, 0.789]	0.695 [0.645, 0.745]

Table A6. *Cont.*

Construct Pair	MLR φ [95% CI]	WLSMV φ [95% CI]
PAIA–BL	0.701 [0.612, 0.789]	0.697 [0.642, 0.752]
PAIA–SAT	0.690 [0.610, 0.770]	0.687 [0.640, 0.735]
PAIA–BT	0.675 [0.592, 0.758]	0.651 [0.598, 0.705]

Note. φ = standardized latent correlation. Confidence intervals are Wald intervals based on robust standard errors. Pairs are ordered by the MLR estimate. MLR and WLSMV as in Tables A4 and A5. In the column headers, CI denotes confidence interval. Construct abbreviations as in Table 4.

Appendix C. Sensitivity Analyses

Table A7. Structural-path sensitivity after excluding BL4.

Path	Primary β	Primary *p*	BL4-Excluded β	BL4-Excluded *p*
PAIA → BT	0.578	<0.001	0.579	<0.001
PAIA → SAT	0.081	0.006	0.081	0.006
PAIA → CON	0.624	<0.001	0.624	<0.001
BT → BL	0.333	<0.001	0.284	<0.001
BT → SAT	0.306	<0.001	0.307	<0.001
BT → CI	0.144	<0.001	0.145	<0.001
SAT → BL	0.179	0.003	0.207	0.001
SAT → CI	0.705	<0.001	0.704	<0.001
CON → SAT	0.581	<0.001	0.581	<0.001
CON → CI	0.018	0.763	0.018	0.769
CI → BL	0.394	<0.001	0.413	<0.001

Note. β = standardized path coefficient; *p* = *p*-value; BL4 = fourth brand-loyalty indicator. Construct abbreviations as in Table 4.

Excluding BL4 did not alter the direction or statistical significance of any structural relationship. Relationships unrelated to the brand-loyalty equation were virtually unchanged; the three coefficients predicting brand loyalty changed modestly in magnitude. The sensitivity analysis therefore indicates that the substantive structural conclusions are robust to exclusion of BL4.

Table A8. Selected measurement-model changes after excluding BL4.

Statistic	Primary Model	BL4 Excluded
Brand loyalty α	0.782	0.815
Brand loyalty CR	0.860	0.890
Brand loyalty AVE	0.610	0.729
HTMT: BT–BL	0.888	0.849
HTMT: CI–BL	0.891	0.898
HTMT: CON–SAT	0.934	0.934
HTMT: SAT–CI	0.907	0.907

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted; HTMT = heterotrait–monotrait ratio of correlations; BL4 = fourth brand-loyalty indicator. Construct abbreviations as in Table 4.

To examine sensitivity to the confirmation–satisfaction distinction, the structural model was re-estimated with their seven indicators combined into a post-use evaluation construct (EVAL). The paths internal to the original confirmation–satisfaction specification (CON → SAT and CON → CI) are absent in this model (Table A9). The BT → CI, BT → BL, and CI → BL coefficients were similar in magnitude across specifications. PAIA showed a substantial total association with SAT in the main model (0.621) and with EVAL in the combined model (0.646). Because SAT and EVAL are different outcomes, these coefficients

are reported descriptively and do not establish equivalence or a redistribution of the same effect. The combined model does not separately estimate confirmation and satisfaction and therefore cannot independently corroborate the confirmation-specific mediation interpretation. That interpretation remains tentative, given the construct overlap and the cross-sectional design.

Table A9. Structural coefficients in the main model and in the model combining confirmation and satisfaction.

Relationship	Main Model β [95% CI]	Combined Model β [95% CI]
PAIA → BT	0.578 [0.499, 0.649]	0.579 [0.498, 0.649]
PAIA → SAT/EVAL, direct	0.081 [0.022, 0.141]	0.302 [0.230, 0.378]
PAIA → SAT/EVAL, total	0.621 [0.543, 0.689]	0.646 [0.570, 0.713]
BT → SAT/EVAL	0.306 [0.231, 0.380]	0.593 [0.514, 0.661]
BT → CI	0.144 [0.065, 0.222]	0.165 [0.083, 0.248]
BT → BL	0.333 [0.247, 0.417]	0.330 [0.242, 0.417]
SAT/EVAL → CI	0.705 [0.593, 0.812]	0.689 [0.608, 0.765]
SAT/EVAL → BL	0.179 [0.057, 0.303]	0.173 [0.059, 0.292]
CI → BL	0.394 [0.280, 0.507]	0.404 [0.289, 0.505]
R^2: SAT/EVAL	0.776	0.651
R^2: CI	0.698	0.676
R^2: BL	0.689	0.689

Note. EVAL combines CON1–CON3 and SAT1–SAT4. Values are standardized coefficients with 95% percentile bootstrap confidence intervals obtained in SmartPLS version 3.2.9 (path weighting scheme, 5000 subsamples, two-tailed). The intervals for both models come from bootstrap runs separate from the run reported in Table 7. Total PAIA associations include the indirect paths through confirmation and brand trust in the main model, or through brand trust in the combined model. SAT and EVAL are different constructs; the corresponding coefficients are compared descriptively. In the column headers, CI denotes confidence interval. Construct abbreviations as in Table 4.

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