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How Does Information Interactivity Promote Customer Trustiness and Positive WOM in AI-Powered Chatbots? Examining Significant Roles of Perceived Values and Active Involvement

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Abstract

The advancement in artificial intelligence (AI)-powered automation has accelerated the integration of AI-powered chatbots into our daily routines, opening novel channels for dynamic information flow and participatory dialogue. Whilst prior studies have examined chatbot interactivity and related outcomes, the mechanism through which information interactivity is translated into relational and advocacy outcomes remains insufficiently theorized, and its conceptual demarcation from active involvement remains underdeveloped. Grounded in Uses and Gratifications (U&G) theory, this study develops and tests a process model of AI-powered chatbot use. In this model, information interactivity is treated as an AI-powered communicative affordance, perceived value represents the mechanism through which gratifications are realized, and active involvement is conceptualized as a situational psychological state that influences customer trustiness and positive word-of-mouth (WOM). Using structural equation modeling on survey data from 588 AI-powered chatbot users, the study finds that information interactivity positively predicts functional, psychosocial, and hedonic value, all of which significantly enhance active involvement. Active involvement, in turn, exerts a significant positive effect on customer trustiness, and customer trustiness significantly promotes positive WOM. By contrast, the direct effect of active involvement on positive WOM is not significant, suggesting that trustiness functions as the more proximal mechanism through which involvement is translated into advocacy. These findings contribute to research grounded in U&G theory by demonstrating how functional, psychosocial, and hedonic value link chatbot interactivity to relational and advocacy outcomes. They also suggest several practical considerations for the development of chatbot services that are more responsive to users' expectations and trustiness formation.

Keywords: information interactivity; perceived values; active involvement; customer trustiness; positive WOM

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1. Introduction

The accelerating pace of automation driven by artificial intelligence (AI) has positioned chatbots as indispensable tools across diverse sectors such as marketing, education, and healthcare [1–3]. As projected by Mordor Intelligence (2023), the global market for chatbots is anticipated to expand from USD 7.01 billion in 2024 to USD 20.81 billion by 2029, corresponding to a notable compound annual growth rate (CAGR) of 24.32% throughout the forecast timeframe. This growth is largely attributable to rising demand for service

automation and continuing advances in natural language processing (NLP) technologies [2]. As a cornerstone of modern customer service strategies, AI-powered chatbots offer distinct operational benefits in real-world applications. By providing prompt responses and efficient support during digital service encounters, AI-powered chatbots can improve service efficiency, customer satisfaction, and user engagement, especially when the interaction is well designed [4,5]. Their ability to handle large volumes of simultaneous interactions further strengthens service performance [6]. As one of the most prominent applications of AI, chatbots are changing how firms interact with customers and are creating new forms of value in digitally mediated markets [7,8]. At a strategic level, AI-powered automation has emerged as a critical enabler of customer communication and relationship-building initiatives [9]. When integrated into customer relationship management (CRM) systems, AI-powered chatbots can improve service coordination while helping firms maintain closer customer connections.

Despite the growing body of research on chatbot interactivity, trustiness, and user responses, significant gaps remain, particularly because contingency, a salient determinant of information interactivity, remains difficult to effectively incorporate into human–computer interaction (HCI) settings [5,10]. First, prior studies have not fully explained how information interactivity in AI-powered chatbot settings is converted into relational and advocacy outcomes through psychologically meaningful processes. Much of the existing work has concentrated either on technological characteristics or on broad attitudinal outcomes [11], leaving the intermediate gratification process underdeveloped. Second, the conceptual boundaries between information interactivity and active involvement remain blurred in the chatbot literature. As a result, it is often difficult to determine whether user responses arise primarily from system properties, value judgments, or more immersive psychological states. This theoretical ambiguity gives rise to an important contradiction in service-oriented industries: although prior studies have shown that perceived service quality is central in determining chatbot effectiveness and customer retention [12], customer engagement with this technology continues to vary considerably [11]. This inconsistency suggests that perceived value, although widely recognized as an important explanatory factor [13,14], has not yet been adequately theorized under conditions where interaction boundaries remain conceptually blurred. Therefore, unpacking the formation mechanism of perceived value under blurred interaction boundaries represents a critical step toward understanding user satisfaction and sustained usage intention.

Recent developments in AI have broadened the explanatory scope of Uses and Gratifications (U&G) theory, which continues to serve as a major theoretical perspective for understanding technology engagement grounded in users' need-driven motives [15,16]. As a prominent sociological framework, U&G views users as active agents who selectively engage with media and communication channels in order to satisfy psychological and social needs [17,18]. AI chatbots are particularly well suited to examination through the lens of U&G because they are not merely technical tools, but intelligent conversational systems with mediating, interactive, and relational attributes. When interacting with chatbots, users do not passively receive information. Rather, they engage with them for different purposes, including solving problems, obtaining emotional support, seeking companionship, or improving efficiency [19,20]. Through responsive exchanges and sustained dialogue, users may experience functional, socio-emotional, and hedonic gratifications. From this perspective, U&G offers a useful analytical lens for examining how individuals proactively interact with AI-driven chatbots to fulfill personal needs, and how such interactions subsequently shape user attitudes and behavioral outcomes through gratification generation. According to U&G, users engage with social media to fulfill a broad spectrum of needs, including psychological gratification, communication effects, personalization, and incentives [17,18,21].

Compared with explanatory frameworks centered primarily on technology adoption, U&G offers a more suitable perspective for understanding how AI-powered chatbots can assess user motivations and satisfaction more precisely, thereby improving the effectiveness of HCI and enriching the relational capital between users and technology [16,22]. In line with this perspective, recent empirical studies grounded in U&G have shown that social media brand chatbots evoke perceptions of enjoyment, facilitate social interaction, and support information seeking. These gratifications, in turn, enhance brand intimacy, strengthen affective commitment, and increase behavioral intentions toward AI-powered chatbots, including purchase propensity [9].

Given these considerations, this study develops and empirically tests a model grounded in U&G theory, in which information interactivity is conceptualized as an AI-enabled communicative affordance, perceived value as the mechanism through which gratifications are realized, and active involvement as a situational psychological state that subsequently influences customer trustiness and positive word-of-mouth (WOM). By conceptualizing perceived value as a multidimensional construct comprising functional, psychosocial, and hedonic value, this study explains how AI-powered chatbots can simultaneously satisfy different user needs. In addition, the study distinguishes active involvement from broader notions of engagement by emphasizing users' concentrated attentional and motivational immersion during chatbot interaction. Accordingly, this study makes three contributions. First, it extends U&G to AI-powered chatbot contexts by showing that gratifications arise not only from content consumption but also from contingent, dialogic, and adaptive interaction with an intelligent nonhuman agent. Second, it advances the chatbot and HCI literature by unpacking the multidimensional value pathway through which information interactivity translates into active involvement. Third, it clarifies the sequential mechanism linking involvement to advocacy by demonstrating that trustiness, rather than involvement alone, is the more immediate driver of positive WOM in AI-mediated service encounters.

The remainder of this paper proceeds as follows. Section 2 reviews the relevant literature and develops the theoretical framework and hypotheses. Section 3 presents the research methodology, including the sampling procedure, measurement development, and analytical strategy. Section 4 reports the empirical results. Section 5 discusses the findings and their theoretical and practical implications. Section 6 concludes by outlining the study's limitations and directions for future research.

2. Literature Review and Hypotheses Formulation

2.1. Linking Information Interactivity to Perceived Values

Rapid technological advancements have substantially enhanced the capacity for interactive communication between individuals and chatbots [3,23]. In contrast to earlier online environments, where interactions with information were more restricted, customers now access information through a range of technological functionalities across diverse contexts and platforms [24]. Accordingly, information interactivity has assumed a more advanced form, as interactions are no longer confined to clicking, browsing, or selecting predefined options. Instead, users engage in conversational, adaptive, and iterative exchanges with systems that can interpret previous inputs, generate contextually relevant responses, and approximate human-like dialogue [25,26]. A growing body of research suggests that interactivity plays a critical role in human-chatbot communication by sustaining responsive exchange and fostering favorable user outcomes. Information interactivity is theorized as a form of reciprocal communication, wherein the emphasis is placed on the relevance of responses from interacting entities [27]. Research across multiple fields consistently shows that the degree of information interactivity significantly shapes users' attitudes,

behaviors, and purchase intentions. For information interactivity to be effectively realized, it is essential for the communication roles to be interchangeable, with interactants engaging in responses that are contextually relevant and relationally meaningful [27]. Within the U&G framework, this form of interactivity matters because users engage with AI-powered chatbots in a purposive rather than passive manner. They turn to these systems to meet particular needs, including information seeking, emotional reassurance, uncertainty reduction, and enjoyment [20]. Information interactivity should therefore be understood as more than a technical property of the system; it also shapes whether users experience the interaction as worthwhile, relevant, and rewarding [10]. Moreover, empirical studies indicate that enhanced information interactivity on digital review platforms substantially strengthens the connection between transmitters and receivers, positively influencing individuals' behavioral intentions [23].

Perceived value is a concept grounded in individuals' subjective evaluations, referring to the criteria they use to gauge the value embedded in a service or product [13,14]. It primarily involves a comparison between perceived benefits and perceived sacrifices, which constitutes a key determinant of individuals' decisions to engage with a particular good or service [28]. In the present study, perceived value is positioned as the post-interaction appraisal through which gratifications are realized. Consistent with the U&G perspective, users initiate interaction with AI-powered chatbots because they anticipate some form of need fulfillment. Following the interaction, they evaluate whether the experience has delivered meaningful benefits. We conceptualize this evaluative outcome as perceived value. This treatment allows perceived value to function as the mechanism linking the chatbot's interactive capability to users' subsequent psychological involvement [20,29]. In line with U&G and the multidimensional nature of chatbot use, this research conceptualizes perceived value as comprising three dimensions: functional, psychosocial, and hedonic value. Functional value refers to the utility users perceive on the basis of a product's quality and expected performance, and it has been identified as a primary driver of user choice [30]. This dimension is closely linked to factors such as functional quality and price utility. Psychosocial value is conceptualized as a social-psychological dimension that hinges upon a product or service's ability to evoke emotional or affective states. It encompasses the emotional comfort and satisfaction that individuals derive from online social interactions and support [29], and is believed to contribute to psychological well-being [31]. Hedonic value pertains to the recreational and pleasurable aspects of interacting with a product or service, including the enjoyment, excitement, and curiosity such interaction generates [14]. This dimension captures the pleasure and emotional gratification users derive from interacting with technologies such as AI-powered chatbots or from entertainment-oriented activities enabled by these services. Such a multidimensional view is particularly relevant in chatbot settings, where users often rely on AI systems for more than one purpose at a time [20–22]. In a single interaction, a chatbot may assist with task completion, alleviate uncertainty or loneliness, and simultaneously provide an enjoyable conversational experience. Therefore, treating perceived value as a multidimensional gratification construct offers a more theoretically precise explanation of how information interactivity shapes downstream outcomes.

Within the domain of HCI, perceived value underscores individuals' personal evaluation of the value they derive from interacting with AI-powered chatbots, where they weigh the perceived values against the costs incurred. This concept is pivotal in influencing the dynamics of HCI. A substantial body of literature has consistently demonstrated that information interactivity on social media aids individuals in gaining value and making decisions [8,11,32]. More specifically, the level of interactivity in AI-powered chatbot interactions significantly enhances the functional value for users, primarily through dynamic,

two-way communication that not only boosts users' perceived competence in problem-solving but also enhances the personalization of responses [7,19,33]. Previous research has also shown that information exchange between AI-powered chatbots and users shapes perceived empathy, thereby enhancing experiential and psychosocial value [11]. Generally, the perceived value of a product increases when users exhibit an intention to engage with it repeatedly. Furthermore, we posit that the interactivity of a mobile application plays a decisive role in augmenting their hedonic value. In e-commerce environments, customers who derive multidimensional value exhibit a stronger propensity to engage with AI-powered chatbots, whereas those who do not perceive any value are less likely to do so, even when faced with disruptions [8]. Thus, it is reasonable to infer that information interactivity also influences value perceptions within the realm of social AI-powered chatbots. Building upon this reasoning, we hypothesize the following:

H1. *Information interactivity positively influences functional value.*

H2. *Information interactivity positively influences psychosocial value.*

H3. *Information interactivity positively influences hedonic value.*

2.2. Linking Perceived Values to Active Involvement

Research indicates that involvement, a situated psychological stance encompassing cognitive, affective, and behavioral components, is crucial for relationship development [34,35]. Active involvement is generally characterized by a strong motivational orientation toward participating in activities such as information sharing, content generation, and the provision of emotional support to others [10]. In the HCI literature, it is often conceptualized as a subjective and multifaceted experience marked by concentrated attention, temporal dissociation, perceived autonomy, intrinsic enjoyment, and heightened curiosity [36]. In the present study, active involvement refers to a user's focused, motivational, and absorptive psychological investment during interaction with an AI-powered chatbot. It captures the extent to which users become mentally concentrated, attentive, and immersed in the interaction episode. This concept should be distinguished from several adjacent constructs that are often used interchangeably in prior research. First, active involvement differs from information interactivity. Whereas interactivity is a feature of the system or communication process, active involvement refers to the psychological state experienced by the user [20,26]. Second, active involvement is distinct from participation, which typically denotes observable behaviors such as posting, sharing, or clicking. Third, it is narrower than the broader concept of engagement, which often encompasses a more enduring cognitive, emotional, and behavioral connection to a brand, platform, or community [9]. By contrast, active involvement in this study specifically emphasizes attentional absorption and motivational immersion within the immediate chatbot interaction. This distinction is theoretically important because users may interact with a highly responsive chatbot without necessarily becoming deeply involved. Interactivity may create the conditions for involvement, but involvement emerges only when users perceive the interaction as sufficiently valuable to warrant cognitive and emotional investment. In this sense, perceived value provides the motivational basis for active involvement. Prior research likewise suggests that involvement is closely tied to the quality of individual experience in digital communication contexts [11], and that stronger interactive and social connection tends to foster more favorable user responses [17,37]. Accordingly, examining active involvement provides important insight into how individuals cognitively, emotionally, and psychosocially process AI-powered chatbot interactions before translating those experiences into subsequent behavioral responses.

The reciprocal correlation between perceived value and involvement has been widely acknowledged in prior research. Several studies have shown that higher levels of perceived value are associated with a greater propensity for active involvement [35,38]. In the context of AI-powered chatbot interactions, when users form favorable evaluations of a chatbot's interactivity quality, they are more likely to develop positive overall assessments of the chatbot itself [38]. These evaluations, in turn, shape subsequent behavioral intentions, underscoring the pivotal role of perceived value in fostering active involvement. Moreover, when interactions with AI-powered chatbots are perceived as enjoyable and satisfying, users tend to remain engaged for longer periods and devote more time and attention to the interaction [2]. From a U&G perspective, perceptions of utility, emotional reward, and enjoyment can motivate users to sustain their involvement, prolong their participation, and become more psychologically absorbed in the interaction [5]. In this sense, perceived value in AI-powered chatbot contexts is inherently multidimensional, encompassing functional, psychosocial, and hedonic dimensions, each of which contributes to users' overall involvement experience [35,39]. Functional value encourages continued involvement by enabling users to achieve desired outcomes efficiently. Psychosocial value enhances involvement by generating reassurance, emotional comfort, and a sense of relational connection. Hedonic value further deepens involvement by making the interaction enjoyable, stimulating, and experientially engaging [29,39]. This is consistent with the view that active involvement is driven by a combination of intrinsic and extrinsic benefits in service and consumption contexts [37]. Taken together, these insights highlight the importance of delineating the complex relationship between different forms of perceived value and users' levels of involvement, thereby contributing to a more nuanced understanding of how involvement develops in AI-powered chatbot interactions.

Individuals tend to seek maximized value in their decision-making processes, which is reflective of their inclination to optimize outcomes [40,41]. Similarly, users interact with AI-powered chatbots for certain demands, such as executing assigned tasks, detecting users' emotional states, and generating actionable solutions [11]. As a result, when perceived value is high, individuals are more inclined to engage in behaviors that facilitate the acquisition of greater advantages. Moreover, exploring the dynamic between perceived value and active involvement not only facilitates the enhancement of individual experiences but also improves the overall effectiveness of interactivity [36]. This correlation highlights the necessity of designing AI-powered chatbots that prioritize individual well-being, as such designs contribute to greater active involvement and sustained interaction [42]. In consequence, a comprehensive exploration of these multidimensional relationships is essential in order to untangle the complexities inherent in how perceived value influences the degree of involvement within the human–chatbot interaction contexts. When users perceive AI-powered chatbots as credible and valuable sources of functional support, psychosocial reassurance, and enjoyment, they are more likely to become actively involved in the interaction process [36]. Thus, we hypothesize:

H4. *Functional value positively influences active involvement.*

H5. *Psychosocial value positively influences active involvement.*

H6. *Hedonic value positively influences active involvement.*

2.3. Linking Active Involvement to Customer Trustiness and Positive WOM

Customer trustiness in AI-powered chatbots is a pivotal construct in the literature on HCI, digital marketing, and AI-enabled service systems. In broad terms, trustiness has been conceptualized as a multidimensional belief structure involving confidence in

an exchange partner's reliability, integrity, and benevolent intentions [40,43]. Within technology-mediated contexts, trustiness becomes especially important because users must often rely on systems whose underlying processes are not fully transparent to them [6]. In the case of AI-powered chatbots, this issue is particularly salient, as users are required to evaluate not only the functional accuracy of the system, but also the credibility, consistency, and relational appropriateness of its responses during ongoing interaction [33]. Accordingly, customer trustiness in AI-powered chatbots may be understood as users' confidence that the chatbot will provide dependable, accurate, and non-deceptive support in ways that align with their expectations and interactional needs [44]. Given its conceptual intricacy, trustiness in AI-driven chatbots has therefore been identified as a critical variable in customer behavior research, with profound and multifaceted implications across affective, relational, behavioral, cognitive, and psychological domains [43,45]. In the present study, customer trustiness in AI-powered chatbots refers to users' confidence in the chatbot's reliability, integrity, and competence during ongoing interaction. Parallel to customer trustiness, WOM constitutes another critical mechanism influencing customer behavior. WOM refers to the informal, non-commercially driven exchange of information about products or services among individuals, occurring both offline and online [25]. Positive WOM is propelled by favorable experiences and serves as a cost-effective means of promoting products. Its efficacy is closely tied to product success, given that users are more inclined to recommend a product after attaining proficiency and assuredness in its operation. In this sense, positive WOM not only reflects perceived competence but also establishes a benchmark for others' success with the product [46]. WOM has long been a central mechanism of information diffusion, and its influence has expanded substantially in digital environments, where online connectivity allows customer opinions to spread rapidly and widely [47].

Customer trustiness in AI constitutes a pivotal determinant in the domain of HCI, as extensively documented in prior research [6,44]. In the context of AI-powered chatbots, customer trustiness depends on the perceived dependability, credibility, and effectiveness of chatbot performance in facilitating the achievement of users' goals [45]. Unlike many conventional digital interfaces, however, chatbots simulate conversational exchange and relational responsiveness, thereby prompting users to form judgments that are not solely technical, but also social and psychological in nature [22,45]. Prior research has identified a range of antecedents of trustiness in emerging technologies, including information quality, structural assurance, functional consistency, and social communication cues [48,49]. However, much of this work has focused primarily on system characteristics and design-related factors, while paying comparatively less attention to the user's interactional state as a precursor to trust formation. This omission is important because trustiness in AI-mediated services may arise not only from technical performance, but also from the extent to which users become psychologically invested in the interaction process itself [12,26]. From this perspective, active involvement emerges as a theoretically important antecedent of customer trustiness. Repeated and attentive interaction enables users to observe whether the chatbot behaves consistently, responds appropriately, and supports their goals effectively over time [45]. Prior studies have likewise suggested that trust develops through repeated and meaningful interaction, and that user involvement can strengthen relational confidence across technology-mediated contexts [48,49]. Active involvement has also been recognized as a vital component in fostering trustiness in psychotherapeutic processes [1]. In this sense, active involvement creates the psychological and interactional conditions under which trustiness can emerge. Nevertheless, existing research has rarely clarified this mechanism specifically in AI-powered chatbot environments. By positioning active involvement as an antecedent of customer trustiness, the present study extends prior research beyond system-

level determinants and highlights the role of users' interaction-specific psychological states in the formation of trustiness.

Positive WOM is significantly shaped by active involvement, as engaged customers, driven by heightened cognitive processing and emotional attachment, are more inclined to disclose their experience [17,47]. Prior studies on customer involvement suggest that involvement fosters advocacy by strengthening loyalty and relational bonds. Specifically, heightened involvement with a product amplifies the likelihood of individuals disseminating their experiences within their social circles, thus amplifying WOM effects [47]. Empirical research provides robust support for this relationship across diverse contexts. For instance, in the tourism sector, research has established that cognitive, affective, and behavioral involvement on social media platforms significantly predicts electronic WOM (eWOM) behaviors [50]. Similarly, in broader marketing contexts, customer involvement, characterized as a circumstance-specific psychological state distinguished by particular levels of cognitive, sentimental, and behavioral commitment in brand encounters, exerts a substantial influence on WOM outcomes [17]. Customers who develop a strong identification through active involvement are thus incentivized to advocate for it within their social networks, further enhancing positive WOM. Collectively, these insights suggest that active involvement serves as a catalyst for positive WOM by deepening customers' emotional and social connections. Drawing on the above synthesis, the subsequent hypotheses are formulated:

H7. *Active involvement positively influences customer trustiness.*

H8. *Active involvement positively influences positive WOM.*

2.4. Linking Customer Trustiness to Positive WOM

Relationship marketing has become a central element of contemporary business strategy, shifting managerial attention from transactional exchange toward the cultivation of enduring customer relationships [4,51]. This paradigm shift underscores a broader transition in market dynamics, moving away from traditional, product-centric frameworks toward customer-oriented models that prioritize connection and involvement. Given the intangible nature of services, trustiness and WOM communication serve as pivotal mechanisms for evaluating customer satisfaction and fostering loyalty. When customers establish trustiness in AI-powered chatbots, particularly through perceptions of their reliability and integrity, they are more likely to demonstrate sustained commitment and ultimately become advocates [4]. Moreover, the quality of AI-powered chatbot service performs a key role in reinforcing customer trustiness. AI-powered chatbots that deliver accurate, timely, and valuable responses enhance the credibility of the service provider, fostering customer trustiness and amplifying the reach through positive referral behaviors and organic advocacy [44]. Studies conducted by Yang et al. (2015) [52] further highlight the strong influence of positive WOM relative to conventional advertising, particularly in shaping audience perceptions and responses. The dissemination of positive WOM not only extends the visibility but also significantly shapes customer perceptions, encouraging others to engage with its products or services.

A review of prior studies indicates that trustiness plays a pivotal role in shaping positive WOM across a variety of contexts [46,52,53]. For instance, Meilatinova (2021) [53] and Yang et al. (2015) [52] demonstrated that trustiness affects WOM and referral behavior for online businesses, such as social commerce. Similarly, website trustworthiness has been shown to directly affect travel customers' willingness to rely on peer recommendations and to spread positive WOM [46]. Beyond its influence on recommendation behaviors, trustiness has also been identified as a key antecedent of both purchase intention and

WOM intention [54]. Importantly, the role of trustiness is not confined to human-to-human interactions. Emerging research suggests that users may anthropomorphize technological systems, attribute human-like qualities to them, and develop trusting relationships with AI-powered chatbots [4]. In such contexts, trustiness becomes especially important because chatbot interactions often involve uncertainty regarding response accuracy, system reliability, and the handling of personal information [45]. Concerns related to data privacy and the management of confidential information may further heighten users' sensitivity to trust issues, making trustiness a central condition for favorable post-interaction responses. Taken together, these considerations suggest that trustiness may play an equally, if not more, important role in technology-mediated interactions than in traditional service settings. However, given the distinctive characteristics of HCI, the extent to which customer trustiness in AI-powered chatbots translates into positive WOM remains an empirical question. Consequently, the following hypothesis is advanced:

H9. *Customer trustiness positively influences positive WOM.*

3. Methodology

3.1. Research Model

Building upon preceding research on AI-powered chatbots [9,17,18], this study proposes an analytical framework (see Figure 1) to examine the key drivers of customer active involvement and positive WOM. Specifically, it investigates how three dimensions of perceived value (namely functional, psychosocial, and hedonic value) differentially influence customers' active involvement and positive WOM toward AI-powered chatbots.

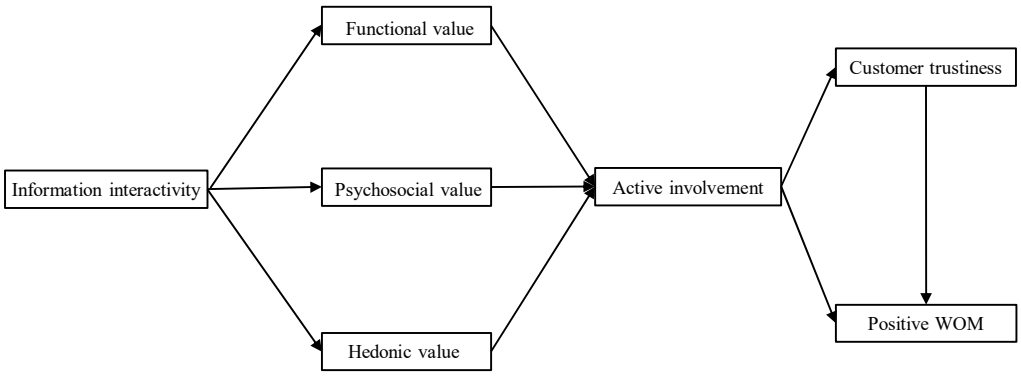


Figure 1. Proposed conceptual study model. Schematic representation of the theoretical framework.

3.2. Data Collection

This study employed a cross-sectional online survey to examine users' evaluations and post-interaction responses to AI-powered chatbots. A survey-based design was deemed appropriate because the focal constructs in the model, such as perceived value, active involvement, customer trustiness, and positive WOM, are inherently perception-based and are best captured through respondents' self-reported evaluations of their lived interaction experiences. Moreover, given the study's objective of testing a theoretically specified nomological network across multiple latent constructs, a structured survey provided an efficient and suitable means of collecting standardized data from a relatively large user population. China provides an appropriate context for this study because AI-powered chatbots are widely used in customer service, education, information search, and social communication. As a result, respondents are likely to have sufficient experience with chatbot-based interactions. Data were gathered through an e-survey administered via Sojump (wjx.cn), a prominent electronic questionnaire platform in China, selected for its

widespread adoption and accessibility among the target population. As a professional survey tool with a substantial user base, Sojump facilitated efficient data collection while ensuring methodological rigor.

A convenience sampling strategy was adopted because no comprehensive sampling frame of AI-powered chatbot users was available, and because the study sought to capture perceptions from actual users who had recent interaction experience with such systems. The survey was open for three weeks, from 2 July to 25 July 2025. To improve sample relevance, only respondents who reported prior experience using AI-powered chatbots were invited to complete the questionnaire. Prior to participation, respondents were informed that their participation was anonymous and voluntary and were instructed to provide honest responses based on their experiences with AI-powered chatbots. The study protocol was approved by the Institutional Review Board of Tianjin University. To incentivize participation, respondents received a monetary reward after finishing the questionnaire. To uphold data integrity, responses that were incomplete or exhibited an implausibly short completion time (i.e., under one minute) were systematically excluded. Following these screening procedures, a final sample of 588 valid responses was retained for analysis. Only these validated responses were included in subsequent analyses. Table 1 presents the descriptive statistics for the research sample. Regarding demographic characteristics, females represented 61.6% of the total participants. The predominant age group was individuals between the ages of 19 and 29, who constituted 60.5% of the respondents. Additionally, undergraduate degrees (including junior college) constituted the predominant educational attainment among participants, accounting for 64.9% of the sample. When examining the duration of AI-powered chatbot usage, a total of 64.5% of participants reported that they had been using such platforms for 1 to 3 years. Furthermore, over half of the participants reported engaging with AI-powered chatbots for no more than one hour per week.

Table 1. Demographic distribution of survey respondents (N = 588).

Categories	Frequency	Percentage (%)
Gender		
Male	226	38.4
Female	362	61.6
Age		
≤18	7	1.2
19–29	361	60.5
30–40	158	29.0
≥41	62	9.3
Educational background		
Middle school or below	5	1.8
High school (including vocational/technical education)	29	4.9
Undergraduate degree (including junior college)	382	64.9
Bachelor's degree (including associate degree)	167	28.4
Years of using AI-powered chatbots		
≤1	102	17.3
1–3	379	64.5
4–6	79	13.4
≥6	28	4.8
Average weekly times of AI-powered chatbot usage		
Under 30 min	145	24.6
30–60 min	221	37.5

Table 1. *Cont.*

Categories	Frequency	Percentage (%)
1–2 h	112	19.0
2–3 h	65	11.1
Over 3 h	45	7.8

3.3. Measurement

The survey instrument comprised two distinct segments. The initial segment incorporated five demographic variables: gender, age, educational background, duration of AI-powered chatbot usage, and average weekly interaction time with AI-powered chatbots. The second segment encompassed six key constructs, previously delineated in the hypothesis development phase. Measurement items were drawn from established studies and adapted to fit the present research setting. Existing scales were used because the purpose of the study was to examine theoretically specified relationships rather than to construct new measures. The choice of instruments was based on their suitability for capturing the focal constructs in the context of AI-powered chatbot use. Information interactivity was measured using items adapted from Sundar et al. [10], as this scale explicitly captures contingency, responsiveness, and message relevance, all of which are central to AI-powered chatbot interaction. The three dimensions of perceived value were adapted from prior research on consumption value and service value [30,31,55], given their close correspondence to the functional, psychosocial, and hedonic gratifications examined in this study. Active involvement was measured using items based on Sundar et al. [10], since these items capture attentional absorption and immersion in the interaction process rather than broader or more enduring forms of engagement. Customer trustiness was measured with items adapted from Kim and Gupta [40], as this scale is well suited to assessing perceptions of reliability, competence, and confidence in an exchange partner within AI-mediated service settings. Positive WOM was measured using established items from prior marketing research [56,57], given their suitability for capturing users' recommendation intentions and favorable interpersonal communication. Table 2 presents measurement items' list and their sources.

Table 2. Model fit statistics for the measurement framework.

Variable	Item	Source
Information interactivity	(1) The AI-powered chatbot's replies maintained continuity with the prior dialogue context. (2) The AI-powered chatbot demonstrated attentiveness to my inputs by providing contextually relevant feedback. (3) I perceived the AI-powered chatbot's responses as tailored specifically to my interactions. (4) The AI-powered chatbot's messages were systematically derived from my earlier inputs.	[10]
Functional value	(1) The AI-powered chatbot demonstrates proficient execution of its intended functions. (2) The AI-powered chatbot consistently provides current and relevant informational content. (3) The information delivered by the AI-powered chatbot is consistently valuable to me. (4) The AI-powered chatbot delivers service of high quality.	[30]
Psychosocial value	(1) Using the AI-powered chatbot enhances how others perceive me socially. (2) The AI-powered chatbot provides dependable services and credible perspectives. (3) Interacting with the AI-powered chatbot strengthens my connections with family, friends, and social networks.	[31]

Table 2. *Cont.*

Variable	Item	Source
Hedonic value	(1) Interacting with the AI-powered chatbot is an enjoyable experience. (2) Engaging with AI-powered chatbot brings me considerable pleasure. (3) I find using the AI-powered chatbot to be pleasurable.	[55]
Active involvement	While interacting with AI-powered chatbot, . . . (1) time seemed to pass rapidly. (2) I often spent longer than originally planned. (3) I could effectively disregard external distractions. (4) my attention did not get diverted.	[10]
Customer trustiness	(1) The AI-powered chatbot I use demonstrates concern for its users. (2) The AI-powered chatbot I use performs its functions competently. (3) The AI-powered chatbot I use is reliable and trustworthy.	[40]
Positive word-of-mouth (WOM)	(1) I would speak favorably about the AI-powered chatbot to other people. (2) I will recommend AI-powered chatbot to someone who seeks my advice. (3) I will actively introduce the AI-powered chatbot I've used to other people.	[56,57]

To mitigate potential confounding influences, critical demographic covariates, specifically gender and age, were implemented as control variables within the analytical model. This methodological refinement served to strengthen both the measurement reliability and construct validity of the investigation. Because the original scales were developed in adjacent digital or service contexts rather than specifically for AI-powered chatbots, all items were contextually adapted to the present setting while preserving their conceptual meaning. This adaptation strategy was adopted to balance contextual relevance with measurement continuity. All constructs were operationalized through a 5-point Likert scale, anchored between "1" ("strongly disagree") and "5" ("strongly agree"). Before the principal investigation, a pilot study was implemented with 15 individuals drawn from AI-powered chatbots user populations. Subsequent to this preliminary phase, the survey items underwent linguistic optimization to improve semantic precision. Furthermore, to rigorously validate the instrument's psychometric properties, the refined questionnaire was subjected to expert review by five communication scholars comprising graduate supervisors and doctoral candidates, thereby ensuring optimal item clarity and conceptual coherence.

3.4. Data Analysis Strategy

IBM SPSS 27.0 and IBM AMOS 28.0 were used for the statistical analyses. Structural equation modeling (SEM) was adopted because the study is based on an integrated theoretical model that includes multiple latent variables as well as direct and sequential relationships among psychological and behavioral constructs. Relative to conducting separate regression analyses, SEM provides a more suitable approach for testing both the measurement properties and the structural relationships simultaneously, while accounting for measurement error. Prior to hypothesis testing, the raw data were screened to eliminate invalid responses and to check for missing values and inconsistencies in response patterns. Subsequently, descriptive statistics were computed with SPSS 27.0 to profile the sample composition and summarize key variable distributions. To rigorously evaluate the proposed hypotheses and the conceptual model, SEM, facilitated by AMOS 28.0, was employed to ascertain the correlations between variables. This approach allowed for the examination of overall model fit, assessment of measurement validity, and construct reliability. To enhance the precision and robustness of the analysis, and to generate more insightful findings, a two-stage analytical procedure was adopted to appraise the proposed framework and its interdependencies. The first stage focused on an in-depth assessment of the measurement structure, while the second stage concentrated on scrutinizing the structural relationships among the constructs. This two-step procedure allowed the measurement model and the

structural model to be evaluated separately, thereby improving the clarity and rigor of the analysis.

4. Empirical Findings

4.1. Measurement Model, Reliability, and Validity

The proposed conceptual framework was evaluated using both absolute and incremental model fit indices. The analytical evaluation yielded supportive evidence across multiple metrics: absolute fit indices, specifically χ^2/d.f. (2.872), GFI (0.902), AGFI (0.929), RMSEA (0.046), and RMR (0.031), each conformed to established psychometric benchmarks. Simultaneously, incremental fit measures including IFI (0.929), CFI (0.939), NFI (0.906), and TLI (0.919) further substantiated the model's alignment with the empirical data. These systematically compiled outcomes, presented comprehensively in Table 3, provide consistent affirmation of the measurement model's acceptable fit. To evaluate the measurement instrument's internal coherence, Cronbach's alpha coefficients and Composite Reliability (CR) estimates were examined. Both reliability indicators exceeded the conventional threshold of 0.70, thereby confirming a satisfactory degree of measurement consistency across all latent constructs. Convergent validity was subsequently examined through a tripartite assessment of standardized factor loadings, squared multiple correlations (SMC), and average variance extracted (AVE). Observed factor loadings demonstrated robust magnitudes measuring between 0.721 and 0.837, with the substantial majority surpassing the recommended 0.70 criterion. Correspondingly, all constructs exhibited AVE estimates significantly above the 0.50 benchmark, and most SMC values similarly surpassed 0.50, collectively reinforcing the measurement model's convergent validity. Complete confirmatory factor analysis outcomes are delineated in Table 4. Most construct pairs fell within acceptable thresholds, although several theoretically proximal constructs exhibited comparatively elevated HTMT values (see Table 5). To complement this assessment, multicollinearity diagnostics were conducted using variance inflation factor (VIF) values for the predictors of the endogenous constructs. For active involvement, the VIF values were 2.434 for functional value, 2.158 for psychosocial value, and 2.079 for hedonic value. For positive WOM, the VIF values for active involvement and customer trustiness were both 1.645. As all VIF values were well below the recommended threshold, multicollinearity was not a serious concern in the present study. Overall, the measurement model shows acceptable fit, satisfactory reliability, and adequate evidence of convergent validity. Discriminant validity is generally supported, although several HTMT values among theoretically related constructs remain relatively high and should therefore be interpreted with caution.

Table 3. Fit indices for the measurement model and structural model.

	χ^2/d.f	GFI	AGFI	RMSEA	RMR	IFI	NFI	CFI	TLI
	<3	>0.9	>0.9	<0.05	<0.08	>0.9	>0.9	>0.9	>0.9
Measurement model	2.616	0.919	0.905	0.042	0.028	0.945	0.918	0.949	0.937
Structural model	2.872	0.902	0.929	0.046	0.031	0.929	0.906	0.939	0.919

Table 4. Statistical outcomes of confirmatory factor analysis.

Constructs and Items	Cronbach's Alpha	Loading (>0.7)	SMC (>0.5)	AVE (>0.5)	CR (>0.7)
Information interactivity (Inf)	0.705			0.840	0.832
Inf1		0.783	0.613		
Inf2		0.756	0.572		
Inf3		0.724	0.524		

Table 4. *Cont.*

Constructs and Items	Cronbach's Alpha	Loading (>0.7)	SMC (>0.5)	AVE (>0.5)	CR (>0.7)
Inf4		0.751	0.564		
Functional value (Fuv)	0.751			0.854	0.853
Fuv1		0.793	0.629		
Fuv2		0.721	0.519		
Fuv3		0.779	0.607		
Fuv4		0.788	0.621		
Psychosocial value (Psv)	0.750			0.747	0.747
Psv1		0.742	0.551		
Psv2		0.735	0.540		
Psv3		0.738	0.539		
Hedonic value (Hev)	0.842			0.842	0.842
Hev1		0.767	0.674		
Hev2		0.812	0.659		
Hev3		0.821	0.588		
Active involvement (Act)	0.743			0.843	0.840
Act1		0.778	0.606		
Act2		0.737	0.543		
Act3		0.790	0.624		
Act4		0.721	0.520		
Customer trustiness (Tru)	0.711			0.848	0.847
Tru1		0.799	0.638		
Tru2		0.816	0.666		
Tru3		0.805	0.648		
Positive word-of-mouth (Wom)	0.836			0.836	0.836
Wom1		0.837	0.575		
Wom2		0.783	0.613		
Wom3		0.758	0.701		

Notes: Inf, Information interactivity; Fuv, Functional value; Psv, Psychosocial value; Hev, Hedonic value; Act, Active involvement; Tru, Customer trustiness; Wom, Positive WOM; SMC, squared multiple correlations; CR, construct reliability; AVE, average variance extracted. CR for internal consistency, Loadings, SMC, AVE for convergent validity.

Table 5. Heterotrait–Monotrait ratio (HTMT).

	Inf	Hev	Psv	Fuv	Act	Tru	Wom
Inf							
Hev	0.845						
Psv	0.803	0.945					
Fuv	0.803	0.862	0.806				
Act	0.669	0.834	0.827	0.829			
Tru	0.852	0.967	0.936	0.834	0.871		
Wom	0.731	0.826	0.826	0.798	0.736	0.932	

4.2. Assessment of Common Method Variance

Common method variance (CMV) constitutes a potential methodological artifact that may emerge when measurement procedures, rather than substantive constructs, account for observed covariance among variables. Given the cross-sectional survey design employed in this investigation, the presence of CMV was methodologically evaluated to ensure the integrity of the observed relationships. To address this concern, Harman's single-factor test was initiated through exploratory factor analysis (EFA) with varimax rotation, incorporating all measurement items from the study. The analysis revealed that none of the factors accounted for a dominant share of the total variance, as the explained variance for each factor remained below the 50% threshold. This suggests that CMV was unlikely to

be a serious problem in the aggregated data. Furthermore, after a rigorous examination of variances in Confirmatory Factor Analysis (CFA) between univariate and multivariate models, the results (multi-factor model: χ^2 = 607.556, d.f. = 231; one-factor model: χ^2 = 1034.827, d.f. = 252; $\Delta\chi^2$ = 427.271, Δd.f. = 21, $\Delta\chi^2/\Delta$d.f. = 20.346, p-value < 0.001) confirm that CMV does not influence the validity of the findings. Taken together, the EFA and CFA results indicate that CMV is unlikely to account for the observed relationships.

4.3. Structural Model

The hypothesized structural model was analyzed utilizing AMOS 28.0, with resulting fit indices confirming a well-fitting framework: χ^2/d.f. = 2.616 (<3), GFI = 0.919 (>0.9), AGFI = 0.905 (>0.9), RMSEA = 0.042 (<0.05), RMR = 0.028 (<0.08), IFI = 0.945 (>0.9), NFI = 0.918 (>0.9), CFI = 0.949 (>0.9), and TLI = 0.937 (>0.9). Following this confirmation, the structural pathways were examined to evaluate the aforementioned hypotheses. Analysis of the standardized path coefficients supported most of the hypothesized relationships. Consistent with initial predictions, information interactivity emerged as a potent positive antecedent of perceived values. Information interactivity was found to be a noteworthy positive indicator of functional value (β = 0.955, p < 0.001), psychosocial value (β = 0.931, p < 0.001), and hedonic value (β = 0.864, p < 0.001), thereby substantiating Hypotheses 1, 2, and 3. Furthermore, each perceived value dimension demonstrated a positive influence on active involvement: functional value (β = 0.402, p < 0.001), psychosocial value (β = 0.203, p < 0.001), and hedonic value (β = 0.294, p < 0.001), supporting Hypotheses 4, 5, and 6. The results further showed that active involvement significantly and positively predicted customer trustiness (β = 0.937, p < 0.001), which in turn significantly predicted positive WOM (β = 0.662, p < 0.001), confirming Hypotheses 7 and 9. However, the direct relationship between active involvement and positive WOM did not reach statistical significance (β = 0.425, p > 0.05), resulting in Hypothesis 8 being rejected. Although these coefficients indicate substantively strong associations, several of them are also relatively high. Accordingly, they should be interpreted as evidence of strong theoretical linkage rather than as proof of complete empirical distinctiveness, particularly in light of the elevated HTMT values reported above for some conceptually close constructs. The empirical outcomes of the hypothesis testing are comprehensively illustrated in Figure 2, with a detailed presentation of path coefficient results available in Table 6.

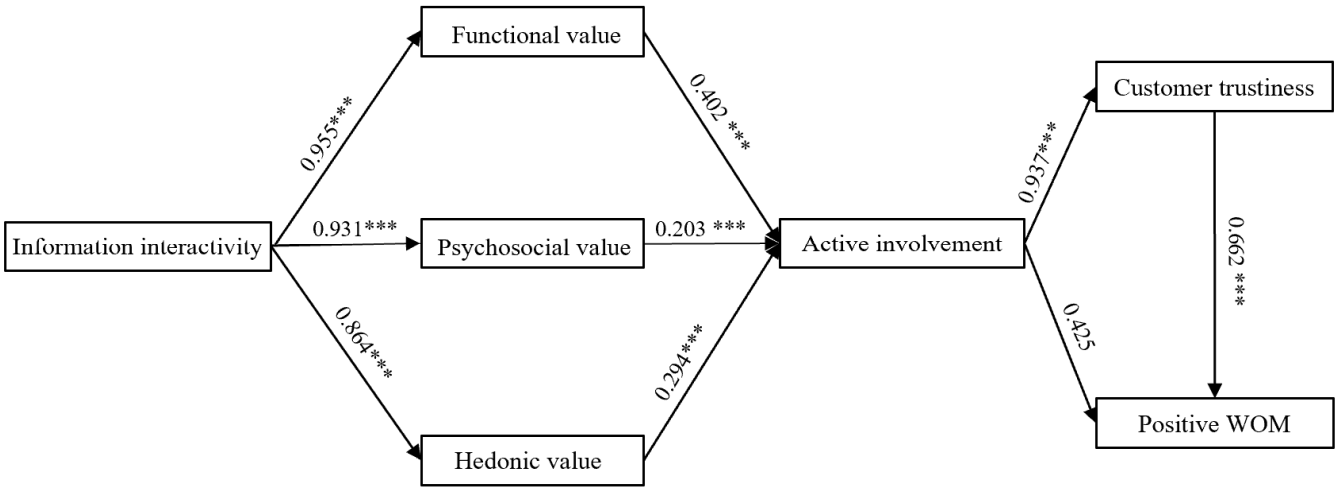


Figure 2. Results for the structural equation model. *** p < 0.001. Structural equation modeling results.

Table 6. Path coefficient estimates of structural model.

Hypotheses	Path	Path Coefficient	*p*-Value
H1	Information interactivity → Functional value	0.955	0.000 ***
H2	Information interactivity → Psychosocial value	0.931	0.000 ***
H3	Information interactivity → Hedonic value	0.864	0.000 ***
H4	Functional value → Active involvement	0.402	0.000 ***
H5	Psychosocial value → Active involvement	0.203	0.000 ***
H6	Hedonic value → Active involvement	0.294	0.000 ***
H7	Active involvement → customer trustiness	0.937	0.000 ***
H8	Active involvement → Positive WOM	0.425	0.133
H9	Customer trustiness → Positive WOM	0.662	0.000 ***

Note: Three asterisks (***) represent $p < 0.001$.

5. Discussion

5.1. Conclusions

This study develops and empirically validates an integrated theoretical framework explaining how the information interactivity of AI-powered chatbots shapes customer active involvement through perceived functional, psychosocial, and hedonic value, and how these processes subsequently foster customer trustiness and positive WOM. By grounding this framework in U&G theory, the study underscores the role of multidimensional perceived value in translating interactive chatbot experiences into relational and behavioral outcomes. These findings contribute to the literature on AI-powered chatbot applications by offering a more nuanced understanding of continued user responses in technologically mediated social environments.

First, the findings show that the information interactivity of AI-powered chatbots positively influences functional, psychosocial, and hedonic value. The findings show that information interactivity positively affects functional, psychosocial, and hedonic value. This result is consistent with prior research showing that interactivity enhances gratification related to social engagement, information acquisition, and entertainment in chatbot interactions [9,17,21]. Compared with prior studies applying U&G in comparable settings, functional value emerged as the strongest dimension in the present study, followed by psychosocial and hedonic value [16]. In this context, the central role of information interactivity in shaping user perceptions resonates with prevailing tenets in HCI research, wherein perceived value accrues from users' subjective evaluation of benefits against costs within AI-powered chatbot interactions [13,28]. Moreover, a user's psychological and emotional resonance emerges as a critical determinant in fostering involvement with AI-powered chatbot interfaces [5,15]. Collectively, these findings suggest that the inherent informational capabilities of AI-powered chatbots can effectively augment users' perceptions of informational and entertainment value, thereby fostering more favorable attitudes and more gratifying experiences.

Second, the data further elucidate that functional, psychosocial, and hedonic value significantly enhance customer active involvement with AI-powered chatbots. Aligning with established academic discourse, the results underscore the capacity of these chatbots to effectively deliver core functionalities [30,31,55]. These encompass crucial elements such as facilitating interpersonal interaction, efficiently conveying information, and providing entertainment, all of which consumers recognize as satisfying their inherent needs and desires. The findings suggest that higher active involvement is associated with stronger psychological connection to AI-powered chatbots. More involved users are more likely to develop intimacy, attachment, and emotional bonding, which, in turn, may strengthen their intention to continue using and recommending the chatbot [21,37]. Consequently,

this pronounced sense of involvement acts as a pivotal catalyst, enriching overall user experience and nurturing the development of constructive human-chatbot relationships. In essence, the perception of value derived from these interactions serves as a direct antecedent to elevated user involvement, thereby affirming its critical role in stimulating active participation and involvement with the AI-powered chatbot service [36]. The study therefore suggests that optimizing these key value propositions, functional utility, positive social interactions, and sources of entertainment, is crucial for fostering meaningful user engagement in the context of AI-driven conversational interfaces.

Third, active involvement was identified as a crucial predictor of customer trustiness, which in turn emerged as a significant determinant of positive WOM. These relationships imply that cultivating active involvement serves as a foundational strategy for building relational capital, ultimately translating into promotional advocacy. The findings are consistent with earlier work conducted by Kang et al., which demonstrated that members develop robust trust and commitment to brands via active involvement [17,18]. However, contrary to our initial expectation, active involvement did not exert a significant direct effect on positive WOM. This non-significant relationship offers an important insight into user responses in AI-powered chatbot settings. Although active involvement reflects attentional immersion and motivational investment in the interaction process, such psychological immersion does not necessarily mean that users are willing to recommend the chatbot to others. Public endorsement requires a further evaluative step, namely whether the chatbot is perceived as sufficiently reliable, credible, and socially safe to justify personal recommendation. In this respect, the present finding is in line with prior evidence suggesting that trustiness may fully mediate the relationship between user involvement and positive WOM [35]. A plausible explanation is that WOM in AI-mediated service settings involves more than a favorable interaction experience. It also entails a form of relational and reputational commitment, because recommending a chatbot implies that users are willing to stand behind its performance in front of others [58,59]. Thus, even when users find the interaction engaging, enjoyable, or absorbing, they may still refrain from recommending the system unless they have developed confidence in its consistency, integrity, and dependability [12,45]. This may be especially salient in AI-powered chatbot contexts, where recommendation behavior can involve perceived social risk, given that users are not only evaluating their own experience but also implicitly endorsing the system's competence to others [58,59]. Taken together, these findings suggest that active involvement should be understood as an important antecedent of trustiness formation rather than as a direct driver of advocacy. Trustiness, in turn, appears to function as the more proximal determinant of positive WOM. This result adds nuance to prior involvement and WOM research by indicating that, in AI-powered chatbot contexts, psychological immersion alone may be insufficient to generate recommendation behavior unless it is accompanied by relational assurance.

5.2. Theoretical Contributions

This study makes several theoretical contributions to the literature on AI-powered chatbots, HCI, and U&G. First, the study extends U&G to AI-powered conversational systems by demonstrating that gratifications in chatbot contexts are generated through contingent and dialogic interaction, rather than through passive exposure to media content alone [22,29]. This extension is important because prior studies have mainly focused on the determinants of active involvement, such as message style, habit, and cognitive factors [36,37,60]. Our findings show that AI-powered chatbots should also be understood as interactive agents whose communicative responsiveness shapes users' gratification processes. Second, although prior scholarship has acknowledged informational and communicative

value as potential drivers of users' active involvement in chatbot interactions [23,28], this study advances the literature by conceptualizing perceived value as a multidimensional gratification mechanism comprising functional, psychosocial, and hedonic value. This perspective provides a more fine-grained explanation of why information interactivity matters. Rather than assuming that interactivity directly produces favorable outcomes, our findings show that users first translate interactive experiences into differentiated forms of value, which then motivate deeper involvement. By distinguishing active involvement from information interactivity and the broader concept of participation [20,34], this study clarifies the process through which active involvement shapes subsequent outcomes. Third, the study refines the process linking interaction experience to advocacy outcomes [14,35]. The non-significant direct effect of active involvement on positive WOM, coupled with the significant effect of trustiness, indicates that psychological immersion alone does not necessarily lead to recommendation behavior in AI-mediated settings. Users appear more willing to advocate for a chatbot only after they have developed confidence in its reliability and integrity. This finding highlights the importance of trustiness as the relational mechanism through which interaction experiences are converted into advocacy outcomes.

5.3. Empirical Ramifications

Beyond the theoretical implications, this study also offers implications for managers, service designers, and organizations adopting AI-powered chatbots. First, the findings indicate that information interactivity plays a meaningful role in fostering customer active involvement and improving relational outcomes in chatbot-based exchanges. For practice, this implies that chatbot design should extend beyond simple responsiveness. More specifically, firms may benefit from developing systems that are better able to interpret conversational context, provide relevant responses in a timely manner, and adjust communicative style in ways that fit users' expectations. Such improvements are likely to support stronger engagement and enable interactions that are more responsive to differences in user characteristics and relational tendencies [60]. Second, the results show that users evaluate AI-powered chatbots through multiple value dimensions. This means that firms should not design chatbot services solely around efficiency or task accomplishment. Instead, a broader service perspective is needed, one that addresses functional value while also taking relational and experiential considerations into account. In practical terms, this may involve offering more personalized recommendations, diversifying conversational functions, and designing interactive features that make chatbot use both useful and enjoyable. By doing so, firms can strengthen the value users derive from chatbot interactions and, in turn, encourage greater active involvement. Third, the findings further suggest that active involvement alone is insufficient to generate positive WOM unless it is accompanied by trustiness. This has direct implications for organizations seeking to leverage chatbots as relationship-building tools. In addition to encouraging engagement, firms should focus on measures that enhance customer trustiness, such as maintaining consistency in performance, clearly explaining what the chatbot can and cannot do, and ensuring adequate protection of privacy and personal data [58,59]. When users view the chatbot as reliable and credible, positive interaction experiences are more likely to be translated into favorable recommendations.

6. Limitations and Future Research Directions

While this study provides meaningful insights into AI-powered chatbot interaction, several limitations should be acknowledged. First, the study relies on a cross-sectional survey design, which limits the ability to make strong causal inferences. This design was retained because the primary objective of the present research was theory testing

in a naturally occurring usage context rather than causal manipulation under controlled experimental conditions. Future studies may therefore employ experiments or longitudinal designs to examine temporal ordering and causal dynamics more explicitly. Second, the study is based on self-reported data from users in China. This study focused on respondents from a single national context in order to maintain contextual consistency and to avoid the confounding effects of cross-cultural differences at this stage of theory testing. However, this choice also limits the generalizability of the findings across cultural settings. Future research should therefore test the model in other national contexts and compare whether cultural differences moderate the relationships observed here. Third, although the measurement model demonstrated acceptable overall psychometric properties, several HTMT values remained comparatively high among theoretically proximal constructs. Likewise, some structural path coefficients were notably large. These patterns may reflect the strong conceptual relatedness of the focal constructs in AI-powered chatbot interactions, but they may also indicate a degree of overlap in how some constructs were measured. Accordingly, the present findings should be interpreted with appropriate caution, particularly with respect to the empirical distinctiveness of closely related constructs. Future research could strengthen construct separation by further refining item wording, employing alternative operationalizations, or combining survey data with behavioral or multi-source indicators. Fourth, although the study concentrates on core psychological mechanisms, it does not consider several other factors that may also shape chatbot-related responses, such as anthropomorphic cues, privacy concerns, task type, or chatbot disclosure. These elements were not incorporated into the current model so that the framework could remain theoretically focused and analytically manageable at this stage. Subsequent research may broaden the model by including these variables and examining whether they alter or qualify the pathway identified in this study. Overall, further work is needed to examine whether the proposed framework holds across different contexts, samples, and research designs.

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