TURNING THE TIDE: HOW AI REVIEW BOT'S REPLY HELPS LOW-FOLLOWER INFLUENCERS IN E-COMMERCE

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ABSTRACT

Previous research has shown that bloggers with larger follower bases typically achieve higher sales, whereas those with smaller follower counts face challenges in enhancing sales. However, limited research has focused on how novice sellers – bloggers with fewer followers - attract consumers effectively. The rise of artificial intelligence (AI) in e-commerce has introduced AI-powered review bots into social media marketing, raising the question: How do AI review bots influence sellers with varying follower counts, especially novice sellers? Study 1 uses data from the platform to empirically validate the positive correlation between follower count and sales performance. Building on this foundation, Study 2 employs an experimental design to explore the moderating effect of AI review bots on this relationship and the mediating role of perceived service quality. The findings reveal that for bloggers with large follower counts, AI-generated replies are generally perceived as generic, diminishing service quality perceptions and reducing purchase intentions. Conversely, for bloggers with fewer followers, AI review bots create a perception of personalized interaction, enhancing perceived service quality and increasing purchase intentions. These findings offer both theoretical and practical implications for leveraging AI technologies to drive consumer behavior in the early stages of seller development.

Keywords: AI review bots; Social media marketing; E-commerce; Follower count; Novice sellers

1. Introduction

With the rapid advancement of information technology, particularly the breakthroughs in AI, the traditional e-commerce industry is undergoing profound transformations. What started as basic web shopping platforms has evolved into sophisticated systems that leverage big data, AI, and machine learning to deliver intelligent product recommendations, optimize customer experiences, and enhance operational efficiency (Nguyen et al., 2022; Ghesh et al., 2024). AI-driven technologies are not only reshaping how businesses engage with consumers, but they are also fostering innovation in business models, enabling companies to better meet consumer needs and stay competitive in

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an increasingly digital marketplace (Iansiti and Lakhani, 2020; Kohtamäki et al, 2019; Sjödin et al., 2020; Sjödin et al., 2021). In this dynamic context, AI technology has emerged as a crucial tool for e-commerce platforms to boost customer satisfaction, enhance user engagement, and ultimately drive sales.

In the context of traditional e-commerce research, much attention has been devoted to exploring how seller characteristics, such as follower count and account reputation, influence consumer purchasing behavior and sales outcomes (Sun et al., 2020; Li et al., 2016). Many studies have established that higher follower counts are associated with increased product sales, as consumers tend to trust and engage more with sellers who have larger followers (Sun et al., 2020; Jin and Youn, 2022). As social media and digital platforms continue to evolve, the ways in which consumers interact with sellers have become more diverse, particularly, the incorporation of AI technology has introduced new perspectives and opportunities for research in this area. Our study focuses on whether the introduction of AI technology can help novice sellers overcome the inherent disadvantages they face in the traditional e-commerce context. Specifically, it examines whether AI technology can provide novice sellers with a competitive advantage, enabling them to compete with more established sellers with larger follower counts. The focus of our study is on AI review bots, a novel AI tool that has been increasingly deployed on e-commerce platforms, particularly in product comment sections. AI review bots are based on a Large Language Model (LLM), which enables them to generate responses by referencing prior consumer reviews and product information on the platform. This design allows the AI bot to provide replies that are similar to consumer reviews. For instance, AI review bots named Robert on Weibo are deployed to automatically reply to user comments with phrases like ‘Thank you for your support!’ or redirect inquiries to customer service. Such bots are increasingly adopted by novice sellers to stimulate engagement. These bots automatically generate machine-written replies to consumer reviews, simulating human-like dialogue, providing real-time feedback, and offering recommendations (Adam et al., 2021; Kushwaha et al., 2021). Despite their growing presence, existing studies focus on AI’s role in general customer service; however, the extent to which AI-driven interactions influence sales—especially across sellers with different follower counts—remains an underexplored area of research. Specifically, the role of AI review bots in moderating the relationship between follower count and sales for novice sellers remains largely unexplored. This study focuses on how AI review bots can help new or lesser-known sellers, who typically have fewer followers, enhance their sales performance by moderating the positive effect of follower count on sales. Addressing this gap provides an opportunity to examine how AI review bots shape consumer purchase intentions and offer strategic advantages to sellers across different levels of followers, with a particular focus on novice sellers. Therefore, this study addresses these questions by focusing on the following specific research question:

RQ1: How can new sellers with limited followers enhance their sales? Specifically, can AI review bots moderate the positive effect of follower count on sales?
RQ2: Why might AI review bots influence the relationship between follower count and sales?

To address these questions, this study investigates the role of AI review bots in moderating the effect of follower count on consumer purchase intentions, focusing especially on their influence on novice sellers. Additionally, it explores how perceptions of service quality mediate this relationship. For sellers with large follower bases, AI-generated replies may be perceived as generic, potentially diminishing the perceived service quality of interaction and reducing purchase intentions. Conversely, for sellers with smaller followers, AI review bots may create a sense of personalized engagement, enhancing service quality perceptions and increasing purchase intentions. This study offers theoretical and practical implications. By focusing on sellers with fewer followers, specifically novice sellers, this research contributes to the growing literature on AI-driven e-commerce by providing insights into how these technologies can help new or lesser-known sellers overcome their initial disadvantages. In addition, this study extends signaling theory by showing that AI-generated responses function as hybrid signals, dynamically interacting with traditional signals like follower count. Practically, this study offers guidance to e-commerce platforms on how to attract and support new sellers, particularly in the design and deployment of AI review bots to enhance customer satisfaction and drive sales growth. However, for mature sellers, it is important to recognize that the use of generic AI review bot responses may no longer be effective. For platforms, it is crucial to consider how AI review bots can be customized to reflect the unique characteristics of each seller, ensuring that responses are personalized while still benefiting from the efficiency of AI-driven interactions.

This paper is structured as follows: Section 2 provides a review of the relevant literature, particularly in relation to the application of AI in e-commerce. Section 3 presents the theoretical framework and hypotheses development, explaining the mechanisms by which AI review bots may affect sales outcomes for sellers with different follower counts. Section 4 details the research methods, including the empirical tests and experiments conducted to test the proposed hypotheses, as well as the empirical analysis and results. Section 5 discusses the findings, highlighting theoretical and practical implications, and Section 6 provides the limitations of this study and directions for future research.

2. Literature Review

2.1. Signaling Theory

Signaling theory provides a framework for understanding how information asymmetry can be mitigated in buyer-seller relationships, particularly in online markets (Kirmani and Rao, 2000; Mavlanova et al., 2016). The theory involves three core components: the sender, the signal, and the receiver (Wells et al., 2011). The sender, typically the seller in e-commerce, uses signals to convey information to the receiver (the buyer) in order to influence their decision-making. These signals help reduce perceived uncertainty by providing cues about the quality or reliability of the seller and product, which in turn reduces information asymmetry and influences consumer behavior (Kirmani and Rao, 2000).

On traditional online shopping platforms, sellers utilize various signals to alleviate buyer uncertainty, such as money-back guarantees (Li et al., 2019), advertising (Kirmani, 1990; Chen et al., 2023), and online word of mouth (Cheung et al., 2014). For example, a high reputation and large follower count on a platform serve as positive signals that foster consumer trust and increase purchase intention (Valsesia et al., 2020). Information asymmetry in e-commerce stems from the buyer's inability to physically inspect products, the physical distance between the buyer and seller, and the time delay between purchase and product receipt (Li et al., 2019; Mavlanova et al., 2016; Mavlanova et al., 2012). Such factors intensify perceived uncertainty regarding seller and product quality (Dimoka et al., 2012). Therefore, online sellers employ both high-cost and low-cost signals to build consumer trust (Spence, 1978). High-cost signals—such as offering free return shipping—require significant financial investment from the seller, enhancing credibility and consumer trust. Buyers who receive this signal know that they can return items without shipping costs if dissatisfied, which increases their purchase willingness (Li et al., 2023). Conversely, low-cost signals, like advertising copied across other sellers, require minimal effort and investment, which buyers interpret as negative signals, potentially reducing purchase intention. Thus, signaling plays a crucial role in e-commerce by shaping consumer trust and purchase behavior.

In traditional e-commerce, signals such as follower count, seller reputation, and customer reviews serve as proxies for quality and reliability (Kirmani & Rao, 2000; Mavlanova et al., 2016). With advancements in technology, e-commerce platforms have begun using digital human anchors and AI-generated tools (Dwivedi et al., 2023; Ge et al., 2021), creating new forms of signals distinct from traditional seller-driven signals. The advent of AI review bots introduces a new class of signals—automated and consistent engagement—that interacts with traditional signals in complex ways. For low-follower sellers, AI-generated responses compensate for weak traditional signals by demonstrating responsiveness and professionalism, thereby reducing perceived uncertainty (Adam et al., 2021; Packard & Wooten, 2013). Conversely, for high-follower sellers, repetitive AI replies may diminish their strong traditional signals, as consumers may perceive a high volume of templated replies as a sign of low service quality and therefore expect more personalized interactions (Jing et al., 2018). This dynamic interplay between AI and traditional signals represents a novel contribution to signaling theory, particularly in the context of hybrid signaling in digital markets (Chen et al., 2023; Libai et al., 2020). However, research on how the interaction between these AI-generated and traditional signals influences buyer behavior remains limited. Therefore, our study investigates how sellers with different follower bases use AI review bots to respond to customer feedback affects purchase intentions. We aim to understand whether AI-generated content, as a novel signal, can enhance users' purchase intentions with traditional signals in this emerging context

2.2. AI-Powered Technology

The rise of AI technology is profoundly transforming various fields, including medicine, law, and business (Ameen et al., 2021). AI refers to the simulation of human behavior by computers, which, through data training, generates outcomes that mimic human thought processes and uses these results to execute complex instructions (Libai et al., 2020). In the context of e-commerce, the introduction of AI has significantly reshaped the online shopping experience by transforming user engagement, changing users' shopping patterns, and influencing purchase decisions and intentions (Foroudi et al., 2018; Cheng et al., 2023). AI applications in online shopping are diverse, encompassing intelligent customer service bots, AI voice assistants, virtual fitting tools, and smart shopping guides (Ameen et al., 2021; Balakrishnan et al., 2024; Chopra, 2019). The utilization of these AI tools aims to enhance users' shopping convenience and interaction with sellers, making the online shopping process more personalized and efficient. However, existing research shows mixed findings on the impact of AI on user behavior. On one hand, AI can help merchants and platforms achieve notable cost savings, boost productivity, and enhance user experiences by offering personalized recommendations and quick responses (Gursoy et al., 2019; Shankar et al., 2018). Such AI tools simplify purchasing decisions for consumers, fostering greater trust in the platform. On the other hand, consumers feel a certain aversion to algorithm-driven AI, with distrust toward its recommendations (Han et al., 2023). Particularly in the context of requiring highly personalized service, AI is not able to provide the emotional support and understanding that human customer service offers. In fact, when AI and human services coexist, consumers often prefer the traditional human interaction model in most cases (Choi et al., 2024).

This study focuses on AI review bots—specifically, bots that sellers use to automatically respond to user comments on social media platforms. As the name of AI review bots suggests, their content is generated by learning existing consumer reviews and the database on the platform, as well as pre-defined customer service scripts. Unlike traditional customer service bots (Chopra et al., 2019), which typically engage in one-to-one interactions, AI review bots in this study operate in a public comment section, automatically responding to user comments in an open, visible way. This public engagement not only provides feedback to commenters but also has effects on other potential customers who observe the interaction. For all consumers, AI review bots engage with them in three stages, including pre-sale, during sale, and after sale. For potential consumers, they interact with AI review bots in their pre-purchase stage. Specifically, AI review bots are automated robots designed to engage with all consumer comments across various stages of the transaction process, including pre-sale inquiries (e.g., questions about product features) from potential consumers, during-sale interactions (e.g., order status updates), and post-sale feedback (e.g., reviews about the product) from existing consumers. In our study, we specifically focus on the potential consumers, therefore, it is pre-sale stage of transactions from the perspective of potential consumers, as this is when potential consumers are most likely to form perceptions of service quality based on interactions in the public comment section and evaluate sellers based on responsiveness and engagement (Adam et al., 2021; Kushwaha et al., 2021). For example, AI review bots respond to questions such as "Does this jacket run small?"—a pre-sale concern from potential consumers, and "This jacket is really great value for the price—I bought two!" —a after-sale comment from existing consumers, to simulate real-world scenarios where potential buyers evaluate sellers based on responsiveness and engagement in their pre-purchase stage (Adam et al., 2021; Kushwaha et al., 2021). Additionally, AI review bots offer a cost-effective solution. They provide instant, consistent responses that signal a seller's commitment to customer service, even if the replies are templated. This aligns with signaling theory, where AI-generated responses act as low-cost signals that reduce information asymmetry (Kirmani & Rao, 2000; Mavlanova et al., 2016).

Previous studies on customer service bots have explored their impact on user behavior and decision-making in various contexts, showing that while customer service bots can enhance users' empathic experience, they may have a limited impact on improving service evaluations (Han et al., 2023). Our research thus examines the potential positive impact of AI review bots in public, interactive settings—specifically, whether these bots can improve purchase intention in conversations that are visible to all users. In contrast to most previous studies, which emphasized the negative impact of customer service bots (Hill et al., 2015; Luo et al., 2019), we aim to explore the unique potential of AI review bots in public social interactions. This approach offers a fresh perspective on understanding the advantages and limitations of AI applications in e-commerce.

2.3. Perceived Service Quality

Perceived service quality refers to users' overall evaluation of their interactions with a service and is widely recognized as a fundamental determinant of purchase intention (Han et al., 2023). Interacting with customers generates value and profitability (Sargeant and Mohamad, 1999). The concept of perceived service quality encompasses both tangible and intangible dimensions. The tangible dimension includes aspects such as reliability, responsiveness, and the physical appearance of facilities (Parasuraman et al., 1985). These elements reflect the structural and procedural aspects of service delivery. On the other hand, the intangible dimension focuses on interpersonal elements, such as the care, politeness, and empathy demonstrated during the service process (Johnston, 1995, 1997). While the tangible aspects provide the foundation for functional service delivery, the intangible aspects are critical for shaping emotional and subjective evaluations, which are integral to perceived service quality. Together, these dimensions create a comprehensive framework for understanding how users evaluate service interactions and provide essential guidance for businesses aiming to enhance customer experiences.

In the context of e-commerce, responsiveness has been identified as a key factor as it reflects the human-centered essence of digital platforms (Lee et al., 2000). Users value timely and effective communication when engaging with online customer service, as the lack of face-to-face interaction necessitates higher expectations for digital responsiveness. For instance, the speed of responses from customer support systems, the accuracy of personalized recommendations, and the thoroughness of product descriptions all play crucial roles in shaping users' perceptions of service quality (Belem et al., 2020; Jing et al., 2018; Nguyen and Hsu, 2022; Ko and Leem, 2004). Moreover, since e-commerce platforms cannot deliver physical products immediately, the quality of communication and interaction becomes even more significant, highlighting the importance of responsive and engaging online service processes.

The emergence of AI technologies has introduced a new dimension to the exploration of perceived service quality. AI review bots, which provide automated and instantaneous responses, have the potential to reshape user interactions with online services. By addressing challenges such as delayed human responses, these bots contribute to more efficient service delivery. However, whether these interactions are perceived as high-quality by users remains unclear. On the positive side, the immediate and consistent nature of AI review bots may enhance user experiences in contexts where speed and efficiency are prioritized. These features can compensate for limitations in human-provided services, such as untimeliness in response quality or availability. Conversely, the absence of personalized responses in AI-driven interactions might diminish their perceived service quality, particularly in situations that require emotional understanding or nuanced engagement. This inconsistency underscores the complexity of incorporating AI into service environments and the need for further exploration of how users evaluate such interactions. While existing research has extensively explored the relationship between service quality and user behavior (Song et al., 2012; Liang et al., 2013), most studies have focused on human-mediated interactions. Introducing AI review bots as a service interaction context extends this literature by exploring how automated, standardized responses influence perceived service quality. By examining these dynamics, this research aims to provide new insights into the evolving nature of perceived service quality in the online shopping context.

3. Research Model and Hypotheses Development

3.1. Follower Count and Sales

In the domain of e-commerce, consumers are exposed to a vast amount of information when making online purchasing decisions. This information, which is both rich and diverse, serves as a crucial basis for consumers' judgments and influences their buying decisions to varying degrees. Among the various types of information, the characteristics of the seller, such as the seller's credibility, the number of followers, and the level of interaction on their content, are particularly salient. These factors serve as key indicators of consumer trust. Specifically, the reputation and influence of sellers play a significant role in enhancing consumer trust in both their brand and products, thereby stimulating higher purchase intentions (Chevalier and Mayzlin, 2006; Pavlou and Gefen, 2004). This study focuses on sellers operating on social media platforms, where they promote and introduce products to attract users, drive engagement through comments, and ultimately influence purchasing behavior. In the social media context, factors such as the number of followers, likes, and comments become essential signals that convey the seller's influence, reliability, and popularity to users (Sun et al., 2020; Belanche et al., 2021; De Cicco et al., 2021). These social signals significantly impact users' perceptions and decision-making processes. A substantial body of literature has examined the impact of followers and user interactions on seller sales, with findings consistently indicating that a higher number of followers is positively correlated with increased sales (Jin and Phua, 2014; De Vries et al., 2012).

In this context, our study aims to first validate the relationship between the number of followers and sales performance in the e-commerce setting. Furthermore, we explore the influence of AI review bots, seeking to understand the role that AI review bots play in shaping consumer behavior on platforms. Building upon this framework, we propose the following hypothesis:

H1: A higher number of followers is positively associated with higher sales.

3.2. The Moderating Role of the AI Review Bot

The moderating effect of AI review bots on the relationship between follower count and purchase intention is fundamentally shaped by the asymmetric impact of comment volume on consumer perceptions. For sellers with a high follower count, the large volume of user interactions necessitates AI-generated responses at scale. While this approach optimizes operational efficiency (Kaewrat & Boonbrahm, 2017; Kautish & Khare, 2022), the resulting uniformity of replies (e.g., repetitive "Thank you for your support!") exposes the mechanized nature of engagement. Consumers perceive such templated responses as evidence of one-click systemic automation rather than genuine effort, particularly because high-follower sellers are expected to deliver premium, high-quality interactions (Han et al., 2023). This mismatch between expectations (personalized engagement) and reality (standardized replies) triggers attributions of indifference, eroding the positive influence of follower count on purchase decisions.

In contrast, sellers with a smaller follower base benefit from the scarcity of user comments, which allows AI review bots to maintain a 1:1 thoughtful reply ratio, as if the seller is carefully crafting each reply. Therefore, even templated replies (e.g., "Thank you for your feedback!") are interpreted as deliberate and attentive engagement. The limited number of interactions amplifies the perceived service quality of each response, fostering an illusion of authenticity where automated replies mimic personalized attention. From the consumer's perspective, this universal responsiveness signals the seller's prioritization of customer interaction (Kirmani & Rao, 2000), compensating for the absence of traditional credibility markers such as follower count (Mavlanova et al., 2016). The scarcity of comments creates an attribution of effort to the AI review bots' responses, enhancing perceived service quality and purchase intention, despite the lack of true personalization.

Low comment volume allows AI-generated consistency to be perceived as professionalism, while high comment volume reveals scalability as a potential drawback. Specifically, for low-follower sellers, the scarcity of comments enables AI review bots to convey an impression of sellers' effort, transforming automation into a credible signal of the sellers' dedication. In contrast, for high-follower sellers, the same automation may contradict potential consumers' expectations for exclusivity—where they anticipate personalized, unique interactions—reframing what should be seen as exclusive, personalized engagement into a more transactional, one-size-fits-all response. Based on this reasoning, we propose the following hypothesis:

H2: For the absence of an AI review bot, follower count positively affects purchase intention. For the presence of an AI review bot, the positive effect of follower count on customers' purchase intention is attenuated for low-follower sellers; such an effect is nonexisted or even reversed for high-follower sellers.

3.3. The Mediated Moderating Effect of Perceived Service Quality

For sellers with a large number of followers, the responses provided by AI review bots are perceived as highly standardized and automated. Given the vast number of user comments that need to be addressed, AI responses tend to be seen as templated, lacking personalization. Users can easily recognize the similarity in AI responses to different commenters, which leads to a perception that their individual feedback is not sufficiently important. Individuals expect to be replied to with personalized answers (Jing et al., 2018), which involves receiving responses that reflect their unique reviews rather than uniform, automated replies. As a result, the absence of personalized interaction diminishes the perceived service quality, ultimately lowering their willingness to purchase. Conversely, for sellers with fewer followers, AI review bots tend to provide more personalized responses since the smaller volume of comments allows AI to tailor responses more closely to the needs of each user. This personalized communication fosters a sense of recognition, where users feel that their opinions are truly valued (Ashforth and Rogers, 2012; Eisenberger et al., 2010). In this context, users are more likely to perceive higher service quality, in turn, increases their likelihood of continued interaction and purchasing, as compared to users who may feel unvalued in the context of a seller with a larger follower base. Thus, we hypothesize:

H3: Perceived service quality mediates the relationship between AI-mediated follower count and sales, such that a lower perceived service quality weakens the positive effect of a high follower count on purchase intention. In contrast, when follower count is low, a higher perceived service quality strengthens the positive impact of follower count on sales.

Based on these hypotheses, we present the following research framework (Figure 1).

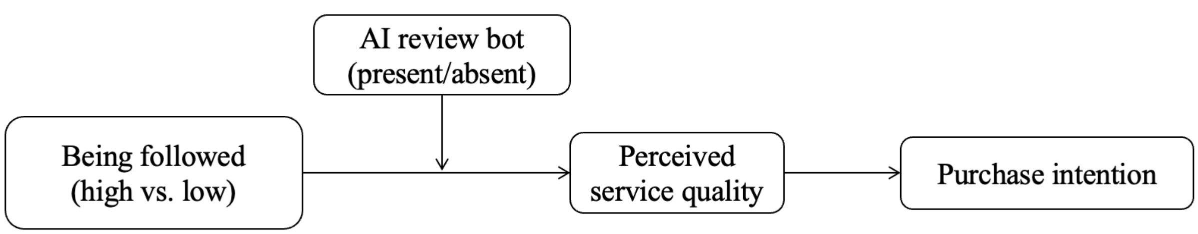

Figure 1. Research framework

4. Methodology

Study 1: Empirical Test

Data Collection

This study utilizes data from both Sina Weibo and Taobao, based on the collaboration between the two platforms, which is a unique relationship enabled by the "Weitao Cooperation" reached in 2013. This collaboration allowed sellers to match their Taobao stores to their Weibo accounts, enabling them to use Weibo as a marketing tool to promote their products to attract consumers. As a result, sellers with both Taobao and Weibo accounts could engage in promotional activities on Weibo, leveraging their follower count to influence purchase behavior on Taobao. That is, Weibo functions primarily as a marketing tool, where the focus is not on direct sales but on building brand presence, while Taobao is a platform primarily for direct sales with less emphasis on marketing. In our study, we focus on the influence of a seller's follower count on Weibo on sales performance on Taobao, a relationship made possible by the integration of both platforms for sellers. Therefore, we match the seller's ID across the two platforms, which allows us to collect data on their Weibo follower count and sales performance on Taobao.

To ensure the representativeness of the sample, we collected 20,000 online sellers on Taobao (www.taobao.com) and Sina Weibo (www.weibo.com), covering 16 distinct product categories, including jewelry, maternal and child products, sports and outdoor, books, audio and video, life services, beauty care, 3C digital products, automotive accessories, and more. This diverse sample captures the wide range of business types on the platforms, ensuring that our analysis is reflective of the variety of sellers using both platforms. The data was collected during the 2015 calendar year, which was chosen because it aligns with the period after the collaboration between Sina Weibo and Taobao, allowing for an accurate analysis of the relationship between follower count and sales performance.

Specifically, automated web scraping techniques were used to collect data from sellers who have both Taobao stores and Weibo accounts, as this allowed us to focus on those who use Weibo for marketing purposes, rather than regular users from Sina Weibo. For each seller, data were collected on store establishment date, location, reputation indicators (including description matching, service attitude, and delivery speed), and consumer reviews (such as the number of positive, neutral, and negative reviews for the past six months and six months ago). Data from the corresponding Weibo account, including follower count, number of followings, account level, and number of posts, were also collected. In total, we initially gathered data for 20,000 sellers. After collecting the raw data, several data-cleaning steps were implemented. First, observations with missing values for key variables, such as follower count, store reputation, or sales data, were excluded from the dataset, resulting in 17,793 valid observations. Second, sellers were required to meet a minimum activity threshold to ensure they were truly active on Weibo. Specifically, sellers needed to have an account level of at least 1, which was based on the seller’s activity, such as login frequency, post volume, likes, shares, comments, and the number of accounts they followed. This ensures that only engaged sellers were included in sample[2], and 17,672 observations remained after this step. Third, we identified and removed outliers in continuous variables, such as sales and follower counts, which could distort the analysis. Finally, a total of 17,097 observations were retained for analysis.

Meanwhile, to ensure the data quality, additional quality control measures were implemented. The scraping process was rigorously tested to minimize errors and ensure comprehensive coverage of relevant seller information across both platforms. And reputation indicators, including description matching, service attitude, and delivery speed, were standardized to ensure consistency in how they were measured across sellers. Finally, we applied the natural logarithm to the sales and follower count variables to reduce skewness.

Variable

The dependent variable in this study is product sales, which serves as the primary indicator of online store performance, influenced by the social media activities of sellers. The independent variable is the follower count of online sellers, which reflects the size and reach of their social network, a crucial element in their social media strategy. To control for other factors that may affect online store sales, we include several key variables based on relevant literature (Dewally and Ederington, 2006; Gao et al., 2016; Wei et al., 2020). First, we consider the Developed Area (DA), which indicates whether the seller is located in a developed area (Beijing, Shanghai, Guangzhou, or Shenzhen), a region with more favorable transportation and distribution channels that can enhance store performance. We also control for the Duration of Store Establishment (DE), as the age of the store is an important determinant of sales, reputation, and brand development. Older stores tend to have more established trust and customer loyalty, which positively influences their performance (Lascu and Zinkhan, 1999; Sheth et al., 1991; Ye et al., 2009). Additionally, we control for the Seller’s Previous Reputation, as a seller's reputation serves as a signal of quality and affects consumer purchase decisions (Dewally and Ederington, 2006; Lascu and Zinkhan, 1999; Melnik and Alm, 2005; Ye et al., 2009), which includes three components (Fassnacht and Köse, 2007; Hausman and Siekpe, 2009; Hwang and Kim, 2007; Mentzer and William, 2001; Xu et al., 2013): Description Matching (DM), which measures how closely the product description aligns with the actual product and reflects the seller’s reliability; Service Attitude (SA), which captures customer satisfaction with the seller’s service, as positive interactions foster trust and loyalty; and Delivery Speed (DS), which reflects customer satisfaction with the delivery process, with faster and more reliable delivery contributing to higher customer retention and sales. Last but not least, we control for following count, post number, and account level of sellers (Valsesia et al., 2020). The definitions and calculation methods of these variables are summarized in Table 1.

[2] The account level ranges from 0 to 32. The Weibo platform calculates this account level internally, and our selection criteria only required that sellers have an account level of 1 or higher, ensuring that they were active on the platform.

Table 1 Variable Definition and Calculation

Variable Name		Variable Symbol	Calculation Method
Dependent Variable	Sales	Sales	LN (actual quantity sold + 1)
Independent Variable	Follower Count	Follower (FR)	LN (follower count + 1)
Control Variable	Following Count	Following (FG)	LN (following count + 1)
	Post Number	Post Number (PN)	LN (post number + 1)
	Account Level	Account Level (AL)	Original data, ranging from 0 to 32
	Developed Area	Deve_Area (DA)	If the seller is located in Beijing, Shanghai, Guangzhou, or Shenzhen, the value is 1; otherwise, 0
	Duration of Store Establishment	Duration_Establish (DE)	The difference between the crawling date and the store's creation date (in years)
	Description Matching	Description_Matching (DM)	Standardized
	Service Attitude	Service_Attitude (SA)	Standardized
	Delivery Speed	Delivery_Speed (DS)	Standardized

Model Specification

We employ a linear regression model to explore the impact of online sellers' social media on product sales. We establish the following regression model. The model specification is as follows:

$$Y = \beta_0 + \beta_1 FR + \delta Controls + \xi,$$

Where Y represents the product sales, β_0 is the intercept, β_1 is the regression coefficient of follower count (FR), and *Controls* represent the control variables, which include factors like the developed area, duration of store establishment, and seller reputation. δ is the coefficient for control variables, and ξ is the error term.

Results

The regression analysis reveals a significant positive relationship between follower count and sales, supporting H1. Specifically, we find that an increase in follower count is associated with higher sales, with the coefficient for follower count (β_1 = 0.27, p < 0.001) being statistically significant. This suggests that social media presence, as measured by follower count, plays a crucial role in driving sales performance on online platforms.

Study 2: Experiment

In **Study 2**, we aim to build upon Study 1 by validating H1 and further examining H2 and H3, which assess the moderating role of AI review bots and the mediating effect of service quality on consumer behavior.

Stimulus Material

To manipulate the presence of an AI review bot, we designed two distinctive replies to scripts to simulate automated responses to user comments within a social media environment (Appendix A). In the AI review bot-present condition, the bot, named "Robot Robert," would provide responses to user comments using these pre-defined scripts. In the AI review bot-absent condition, user comments remained unanswered. These responses were tailored to resemble actual customer service interactions, enhancing validity by mirroring common interactions on digital platforms. The featured product was a jacket suited for all genders (Appendix B), chosen for its relevance to seasonal purchasing needs.

We manipulated the follower count of the blogger as a proxy for social influence. The blogger's follower count was prominently displayed next to their seller's name, differentiated into high-follower (21530 followers) and low-follower (49 followers) conditions (Valsesia et al., 2020). In the high-follower scenario, a higher volume of user comments was presented alongside two groups of responses used to reply to different user comments, simulating an environment of high social engagement. In the low-follower condition, with fewer overall user comments, we designed two user comments and one AI response per comment. This design helped isolate the effect of social influence on purchase intention while adopting replies with the same content in different scenarios.

Procedure

A total of 250 participants recruited from Credamo participated in this experiment. Participants were randomly assigned to one of four conditions in a 2 (AI review bot: present vs. absent) × 2 (follower count: high vs. low) factorial design. Each participant was asked to imagine they were browsing a social platform, such as Weibo, and encountered a blogger recommending a jacket as the weather turned colder. We emphasized the number of followers the blogger had to distinguish between high and low social influence, with follower counts clearly displayed in each scenario.

Participants in the AI review bot-present conditions were introduced to the bot, "Robot Robert," which responded in the comments section, and we provided a brief context on the bot's purpose to facilitate engagement. Participants were instructed to focus on the comments section and reflect on how the interaction might influence their purchase decision. After viewing the product descriptions and comment section, we conducted manipulation checks and measured related variables, including perceived service quality and purchase intention. Measurement items were adapted from validated scales in existing literature, with responses rated on a seven-point Likert scale to ensure consistency. Quality control was maintained via two attention check questions and participant feedback on the perceived realism of the experimental scenario. A comprehensive list of measurement items is provided in Appendix C.

Results

From the total sample, 222 participants passed both attention checks and were included in the final analysis. For the randomness checks, statistical checks (ANOVA for ordinal/continuous variables; chi-square for categorical variables) confirmed no significant differences between groups in age, AI familiarity, or gender (all $p > 0.05$), indicating successful randomization. Detailed results are provided in Appendix D. We then tested H1, which predicted that higher follower counts positively influence purchase intention. As expected, the results indicated a significant difference in purchase intention within different followers ($\beta = 0.38$, $t(112) = 4.342$, $p < 0.001$), with bloggers who had high follower counts leading to greater purchase intention than those with low follower counts, supporting H1.

We used the perceived presence of the AI review bot as a manipulation check, finding that participants successfully recognized the presence or absence of the AI review bot ($M_{absent} = 0.15$ versus $M_{present} = 0.99$, SDs = 0.358 and 0.096, $p < 0.001$), validating the manipulation's effectiveness. To examine H2, which proposed that the AI review bot moderates the effect of follower count on purchase intention, we conducted a two-way ANOVA. The results (Figure 2) show that AI review bots significantly moderated the effect of follower count on purchase intention ($F(1, 218) = 111.5$, $p < 0.001$). Specifically, without AI review bots, follower count has a positive impact on purchase intention ($M_{low\_AIabsent} = 3.286$ versus $M_{high\_AIabsent} = 4.290$, $p < 0.001$). However, the presence of the AI review bot reverses the positive impact of follower count on purchase intention ($M_{high\_AIpresent} = 3.293$ versus $M_{low\_AIpresent} = 5.275$, $p < 0.001$). These results confirm H2.

Figure 2. Interaction effect of follower count and AI review bot in Study 2

For H3, we employed SPSS PROCESS Model 8 (Hayes, 2017) to test the mediating effects of perceived service quality on the moderation effect of AI review bots on the relationship between follower count and purchase intention. Then we tested a mediated moderation model, with follower count as the independent variable, AI review bots as the moderator, perceived service quality as the mediator, and purchase intention as the dependent variable. As shown in Figure 3, there is a significant interaction effect between the follower count and AI review bots on perceived service quality (β = -2.80, t = -10.76, p < 0.001). Specifically, the presence of the AI review bot led to a decline in perceived service quality (β = -0.84, t = -6.47, p < 0.001) for bloggers with high follower counts, which in turn decreased purchase intention (β = 0.52, t = 8.41, p < 0.001). The mediating effect of perceived service quality is positive and has a 95% confidence interval without zero (95% CI = [0.0691, 0.4917] when without AI review bots, and is negative and has a 95% confidence interval without zero (95% CI = [-1.5427, -0.8683] when with AI review bots. These results lend support for H3, showing AI review bots undermine users' perceived service quality, thereby reducing users' intent to purchase for high-follower sellers. In contrast, AI review bots enhance consumers' perceived service quality, in turn, increasing their purchase intention for low-follower sellers.

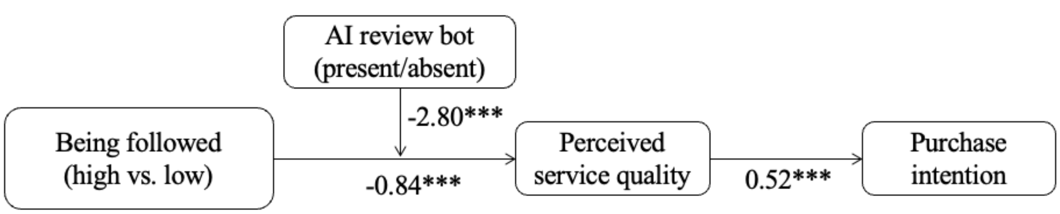

Figure 3. The mediated moderation process

5. Conclusion and Discussion

This study explores the role of AI review bots in the context of social e-commerce platforms, specifically focusing on their impact on novice sellers. Through two studies, we examine how AI review bots moderate the relationship between the number of followers a seller has and consumers' purchase intention.

5.1 Conclusion

In **Study 1**, we use data from social e-commerce platforms in 2015 to validate the positive relationship between follower count and sales. Our findings reveal that sellers with higher follower counts on social media tend to have better sales. This result underscores the importance of follower count as a key factor in the success of sellers on social e-commerce platforms. Building on these findings, **Study 2** investigates the moderating role of AI review bots in the follower-sales relationship identified in Study 1. The results show that AI review bots have a negative moderating effect on this relationship. Specifically, for sellers with a high number of followers, the presence of AI review bots reverses the positive impact of follower count on sales. Conversely, for sellers with fewer followers, AI review bots help mitigate the negative effects of having a smaller follower base, leading to an increase in sales. We further explain these phenomena by examining the mediating role of perceived service quality. In the case of sellers with large followers, AI review bots' automated replies are perceived as impersonal and templated, which leads some users to perceive that the service quality is lower. On the other hand, for sellers with fewer followers, the more attentive nature of the AI-generated responses is appreciated by users, who perceive higher service quality, thus enhancing their purchase intention.

5.2 Theoretical Contribution

This study makes significant theoretical contributions in several areas. First, our study extends signaling theory by showing that AI-generated responses function as hybrid signals, dynamically interacting with traditional signals like follower count. Specifically, we demonstrate that AI signals can enhance the credibility of low-follower sellers by compensating for the lack of traditional social proof, while potentially undermining the credibility of high-follower sellers by failing to meet expectations for personalized engagement. This finding contributes to the expanding literature on hybrid signaling in digital markets, where technological innovations are reshaping the way signals are perceived and interpreted (Chen et al., 2023; Libai et al., 2020).

Second, this study extends the literature on the relationship between seller influence and consumer purchase decisions in the context of traditional e-commerce. Specifically, it fills a gap by exploring how sellers with smaller follower bases can leverage AI review bots to overcome their relative lack of influence. While prior research has shown that a higher number of followers does not always guarantee an increase in consumer purchase intention (Pittman and Abell, 2021), few studies have investigated how novice sellers can use innovative strategies, such as AI review bots, to bridge this gap. Our research not only sheds light on this phenomenon but also provides a new perspective for understanding e-commerce marketing dynamics.

Third, this study reveals the role of AI review bots in e-commerce seller marketing and uncovers the underlying mechanisms. With the rapid advancement of AI technologies, much of the existing literature has focused on AI's role in assisting consumer decision-making (Klaus and Zaichkowsky, 2022; Song and Lin, 2024; Kim et al., 2021). However, there has been limited research on how AI tools, specifically AI review bots, can assist sellers in marketing their products. Our study fills this gap by exploring how AI review bots can enhance sellers' ability to influence consumer behavior, especially in a context involving novice sellers. This novel application of AI technology offers valuable insights into the potential of AI tools as a marketing strategy

5.3 Practical Contribution

This study also contributes to practical implications. For novice sellers, AI review bots offer a promising solution to the challenges of a limited customer base. By enhancing users' perceptions of service quality, AI review bots can help these sellers overcome the initial hurdles associated with having fewer followers, thereby boosting their sales and facilitating their growth. For sellers with large followers, our research provides important guidance. While a high follower count typically results in positive marketing outcomes (Pillai et al., 2020), it can increase user expectations as well. If users feel that the quality of service falls short of their expectations—due to template-like replies—they may reduce their purchase intention. Therefore, sellers with large follower bases should be mindful of over-relying on AI review bots, especially when the quality of the product or service is not sufficiently aligned with user expectations. Overuse of automated responses could ultimately undermine customer trust and lead to negative marketing outcomes.

Finally, for e-commerce platforms, AI review bots offer not only a tool to assist novice sellers but also an opportunity to improve the overall revenue of the platform. Platforms can benefit by further developing and optimizing AI review bot functionalities, offering these tools to a wider range of sellers and thereby attracting new sellers. This could enhance platform engagement and competitiveness. Additionally, platforms should consider providing customized AI review bot services tailored to different types of sellers, thereby maximizing the potential for personalized marketing.

6. Limitation

This study has several limitations that should be acknowledged. First, we limited the scope of our examination of AI review bots to two response templates. In real-world e-commerce settings, sellers may utilize different numbers of response templates. Future research should explore the impact of varying numbers and types of response templates to better understand the most effective design for enhancing user experience and sales performance. Second, mediators such as perceived warmth (Puzakova & Aggarwal, 2018) and perceived value (Zeithaml, 1988) could be explored in future research, although perceived service quality shares similarities with these constructs. We believe that the dimensions of perceived service quality inherently encompass aspects of perceived warmth and perceived value. However, we recognize that investigating the roles of perceived warmth and perceived value as mediators could offer valuable insights, especially in the context requiring deeper emotional connections. Future studies could build on these dimensions to further refine the understanding of AI interactions in e-commerce settings, particularly in fostering trust with novice sellers. Third, we acknowledge that the absence of longitudinal data in Study 1 limits our ability to definitively address the reverse causality issue. Future research could benefit from secondary data spanning multiple years, which would allow for a more robust examination of the causal relationship between follower count and sales. Fourth, this study primarily focuses on the role of AI review bots, assuming that sellers, aiming to reduce operational costs, would rely exclusively on AI-generated responses to user comments. While this is a valid assumption, it does not capture the full complexity of customer service in online marketplaces. Future research should investigate the interaction between human responses and AI-generated replies, examining the potential for both competition and collaboration between these two sources of feedback. Such studies could provide deeper insights into how the combination of human and AI responses affects customer perceptions, seller performance, and overall marketplace outcomes. Fifth, while our study demonstrates the effectiveness of AI review bots using a basic, positive response style to engage consumers, future research could explore the impact of different bot responses styles in more complex contexts, such as problem-solving. Examining these alternative styles could provide additional insights into the broader potential of AI bots in customer service interactions.

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APPENDIXES

Appendix A: Comment Scripts Use in the Experiment

High Followers, with AI review bots	**High Followers, without AI review bots**	**Low Followers, with AI review bots**	**Low Followers, without AI review bots**
Seller Followers: 21530 **Post** *(Appendix B)* **Comment section** User A: "This jacket is really great value for the price—I bought two!" ✧ AI Reply: "Thank you for your support! We hope you like our product!" User B: "I bought it too; the quality is pretty good." ✧ AI Reply: "Thank you for your support! We hope you like our product!" User C: "A friend recommended it	**Seller** Followers: 21530 **Post** *(Appendix B)* **Comment section** User A: "This jacket is really great value for the price—I bought two!" User B: "I bought it too; the quality is pretty good." User C: "A friend recommended it to me." User D: "What occasions is this jacket suitable for?" User E: "Which color of this	**Seller** Followers: 49 **Post** *(Appendix B)* **Comment section** User A: "This jacket is really great value for the price—I bought two!" ✧ AI Reply: "Thank you for your support! We hope you like our product!" User B: "Does this jacket run small in size?" ✧ AI Reply: "Thank you for your feedback! Please reach out to our	**Seller** Followers: 49 **Post** *(Appendix B)* **Comment section** User A: "This jacket is really great value for the price—I bought two!" User B: "Does this jacket run small in size?"

to me.” ✧ AI Reply: “Thank you for your support! We hope you like our product!” User D: “What occasions is this jacket suitable for?” ✧ AI Reply: “Thank you for your feedback! Please reach out to our customer service on Taobao!” User E: “Which color of this jacket is the most versatile?” ✧ AI Reply: “Thank you for your feedback! Please reach out to our customer service on Taobao!” User F: “Does this jacket run small in size?” ✧ AI Reply: “Thank you for your feedback! Please reach out to our customer service on Taobao!”	jacket is the most versatile?” User F: “Does this jacket run small in size?”	customer service on Taobao!”	

Appendix B: Post Content

A jacket for just 99 RMB—cheaper than a T-shirt! Introducing the fall collection: "Couples' Three-in-One Outdoor Jacket"! The weather is still a bit warm, so we weren't planning to release it this early, but the price is just too tempting.

Available in a wide range of colors: black, pink, ivory, khaki, army green, burgundy, camo green, and camo blue. Sizes range from XS to 4XL.

One jacket = outerwear + windbreaker + raincoat! The value is off the charts!

The jacket features a minimalist solid color design with no complicated prints, making it super easy to style. Whether you're dressing casually or aiming for a more polished look, it exudes effortless sophistication.

It truly suits all ages and genders—anyone can look amazing in it!

Appendix C: Variables Measured in the Experiments

Perceived presence of AI review bot:
When reading the comment sections, did the page include replies from a bot?
-Yes
-No
-I don't remember

Perceived service quality (7-point scale): (Cronin et al. 2000)
Please rate the service provided in the comment section for each of the following items below.
-Poor/excellent
-Inferior/superior
-Low standards / high standards

Purchase intention (7-point scale): (Thomas et al., 2019)
-I intend to buy the jacket about which I have read online reviews.

-If somebody asks me for advice on buying a jacket, I recommend the jacket about which I have read online reviews.
-In principle, I would rely on online reviews to gather information before purchasing this jacket.
-In the future, I will buy the jacket about which I have read online reviews.

Appendix D: Randomness Check

Variable	**Condition 1 (AI Absent, High Followers)**	**Condition 2 (AI Present, High Followers)**	**Condition 3 (AI Absent, Low Followers)**	**Condition 4 (AI Present, Low Followers)**	**Test Statistic (*p*-value)**
Age (Mean, SD)	2.54 (0.91)	2.36 (0.64)	2.46 (0.76)	2.58 (0.73)	$F = 0.89$ ($p = 0.45$)
Gender (% Female)	71%	65%	65%	74%	$\chi^2 = 1.58$ ($p = 0.66$)
Prior AI Experience (Mean, SD)	3.19 (0.66)	3.12 (0.60)	3.07 (0.75)	3.26 (0.60)	$F = 0.86$ ($p = 0.47$)

Appendix E: Detailed Experimental Procedures

1. Experimental Design

Type: 2 (AI review bot: present vs. absent) × 2 (follower count: high vs. low) between-subjects design.

Platform: Simulated social media interface (e.g., Weibo-style product page).

Recruitment: Participants recruited via Credamo, a reputable Chinese online panel platform.

2. Participant Instructions

Participants received the following instructions (translated from Chinese):

*"Welcome to our study on user behavior in social commerce! Your responses will remain confidential. This experiment involves three parts:

Demographic and behavioral questions.

Exposure to a simulated social media product page.

Post-experiment measures of service quality and purchase intention.

Please engage carefully, as valid responses will be rewarded."*

3. Procedure

Part 1: Demographic and Behavioral Survey

Collected data on gender, age, AI familiarity.

Part 2: Scenario Setting *(See Appendix A)*

High-Follower + AI: Participants viewed a product page with 21,530 followers and AI-generated replies (e.g., “Thank you for your feedback!”).

High-Follower (no AI): Same follower count with no replies.

Low-Follower + AI: 49 followers with AI replies.

Low-Follower (no AI): 49 followers with no replies.

Example Stimulus *(See Appendix B)*:

"Imagine you are browsing Weibo and encounter a seller promoting a jacket. The seller has [21,530/49] followers. [AI replies are present/absent] in the comments."