IS THE COMBINATION SUPERIOR TO THE SINGLE RECOMMENDATIONS? COMPARING THE EFFECTS OF AI, INFLUENCER, AND THEIR COMBINATION ON CONSUMERS' PURCHASE INTENTIONS

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ABSTRACT

To address limitations in diversity and novelty in AI recommendations, e-commerce platforms are increasingly leveraging influencer recommendations to assist in consumer decision-making. Many online merchants now provide both AI and influencer recommendations to consumers simultaneously. But is the combined recommendation method always the most effective? Existing research requires further insight into this question. This study adopts signaling theory and uniqueness theory, using an experimental approach to compare the effects of AI, influencer, and combined recommendations on online consumer decision-making. The results indicate that both combined and AI recommendations are more effective than influencer recommendations in enhancing online consumers' purchase intentions, with no significant difference between these two types of recommendations. Additionally, it is found that combined recommendations significantly increase purchase intentions more than influencer recommendations for hedonic products, whereas there is no significant difference for utilitarian products. For prevention-focused consumers, combined recommendations exert a greater positive influence than influencer recommendations when purchasing hedonic products, although this difference is not significant for utilitarian products.

Keywords: AI recommendation; Influencer recommendation; Combined recommendation

1. Introduction

In the Web 3.0 era, consumers are facing an unprecedented dilemma of information overload. The number of products on e-commerce platforms has exploded; for instance, according to SellerSprite, Amazon USA has more than 900 million items for sale as of November 2024 (SellerSprite, 2025). Even if consumers have preset their needs in

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advance, they still encounter information overload, making it very difficult to find the best products quickly. Additionally, the complexity of product details and the inconsistency in product reviews further complicate consumers' ability to screen products. This state of information saturation directly challenges consumers' cognitive processing abilities and significantly impacts their decision-making processes, leading to a decline in decision quality (Jacoby, 1984; Sasaki et al., 2011), longer decision times (Peng et al., 2021), increased decision difficulties (Qin and Han, 2009), and reduced decision-making efficiency (Hu and Krishen, 2019). To enhance the efficiency and quality of consumer decisions within limited cognitive resources, major global e-commerce platforms like Amazon, eBay, Taobao, and Douyin are increasingly adopting artificial intelligence algorithms and models to recommend products and services that consumers are likely to be interested in, known as AI-driven recommendations.

AI recommendations represent an advanced form of algorithmic recommendations, evolving from early collaborative filtering algorithms to contemporary deep reinforcement learning models, which illustrate the ongoing development of recommendation systems. Research indicates that AI-driven recommendation systems can enhance decision-making by filtering out irrelevant information, thereby alleviating the cognitive burden of information overload, improving the quality of choices, and increasing consumer confidence (Aljukhadar et al., 2012; Köcher et al., 2019; Isinkaye et al., 2015; Huang and Zhou, 2019). A crucial aspect of AI recommendations in mitigating the information overload associated with online shopping is the platform's ability to manage the number of product options within the limits of human working memory through algorithmic screening. For instance, Tmall analyzes product attribute data and users' historical behavior data through algorithms to identify and recommend other products similar to those the user previously showed interest in, effectively condensing the platform's extensive product range into a streamlined user interface and reducing consumer decision-making time. Research shows that AI-driven personalized recommendations can enhance both the breadth and depth of a consumer's consideration set, resulting in a 12.4% increase in the propensity to buy and a 1.7% rise in shopping cart value (Li et al., 2022). Barilliance, a provider of ecommerce personalization solutions, also discovered that product recommendations on product detail pages accounted for up to 31% of total revenue (compared to an average of 12%) and boosted the likelihood of purchase by 4.5 times (Serrano 2023). However, AI recommendations also present deeper issues. First, collaborative filtering algorithms within recommendation systems tend to limit content diversity and reinforce existing preferences, leading to high similarity among recommended categories and resulting in the "filter bubble" effect (Bellina et al., 2023; Areeb et al., 2023). Second, to sustain short-term click-through rates, recommendation systems often prioritize accuracy and popularity over novelty, which diminishes the newness of recommended products (Massimo and Ricci, 2021; Mendoza and Torres, 2019). This implies that the system often recommends popular items instead of innovative ones, making it difficult for consumers to discover new products within the AI recommendation interface. Balancing accuracy and diversity remain a significant challenge faced by recommendation systems over time (Javari and Jalili, 2015).

In this context, the rise of social commerce has given birth to a new kind of recommendation agent— influencers. With their charm, fan base, shopping experience, and consumer knowledge in specialized fields, influencers recommend a select few suitable products from a wide array for consumers (Belanche et al., 2021; Wentzell, 2021), emerging as a novel form of recommendations. Due to factors such as alignment with consumer values, heightened emotional engagement, and social influence, influencer recommendations typically demonstrate higher conversion rates and consumer engagement compared to traditional advertisements (Belanche et al., 2021; Lou and Chen, 2019; Leung et al., 2022). Influencers tend to choose what they believe are the best products from a wide variety of brands and items based on their richer purchasing experience and expertise in specific fields, thereby narrowing down the consumer's choices to some extent. Moreover, influencers often enjoy significant popularity among their fans, and their recommendations enable consumers to establish cognitive shortcuts that translate the multitude of related products and complex product parameters into trust in the recommender's professionalism. As a result, many traditional e-commerce platforms have begun to incorporate influencer recommendations, providing consumers with a more diverse array of product options. On social commerce platforms, influencer recommendations are frequently presented through videos, images, and text, showcasing personal experiences with the products. Conversely, on traditional e-commerce platforms, due to the nature of the platform, the product recommendation interface remains product-centric, typically noting influencer endorsements next to the products.

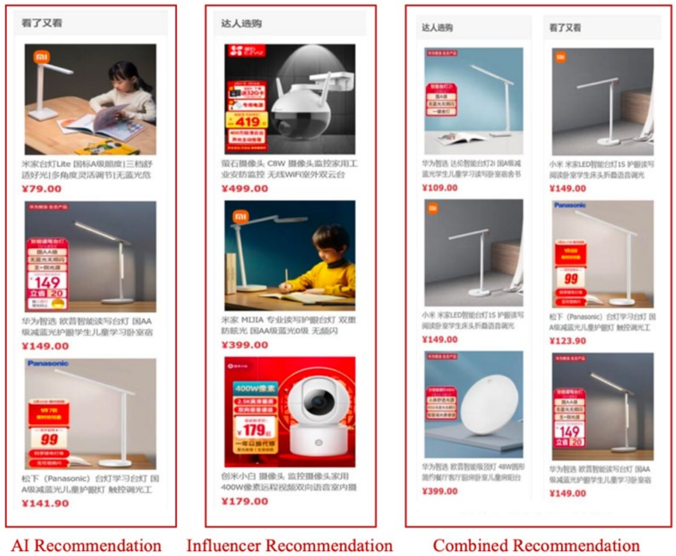

Figure 1: AI recommendation, influencer recommendation, and combined recommendation on JD.com

Recently, e-commerce platforms like JD.com have begun to combine AI recommendations with influencer recommendations, offering consumers what is termed "combined recommendations." For instance, AI recommendations might propose similar colors and styles for a consumer who frequently buys white floor lamps, based on their previous purchase data and personal preferences. In contrast, influencer recommendations arise from the influencer's personal experiences and insights, potentially suggesting different colors and styles of lighting fixtures, as shown in Figure 1. However, whether combined recommendations are inherently superior to individual recommendation methods is still a matter of debate. On the one hand, combined recommendations may create a synergistic effect. By merging content-based recommendations with collaborative filtering (Campos et al., 2010; Çano and Morisio, 2017) or by combining rating-based recommendations with sentiment analysis of reviews (Elahi et al., 2023), hybrid recommendation systems can enhance overall system performance. Moreover, users are more inclined to accept suggestions when the algorithms align with expert opinions, leading to higher decision quality (Xu et al., 2020). On the other hand, combined recommendations can also result in interference effects. When the sources of recommendations are inconsistent, users may encounter information conflict, making it difficult to determine which suggestion is more reliable. This can lead to challenges in decision-making and a decline in decision quality (Xu et al., 2020; Carroll and Sanchez, 2021).

In light of the preceding background, this study utilizes signaling theory and uniqueness theory, conducting three laboratory experiments to compare the effects of AI recommendations, influencer recommendations, and their combination on online consumers' purchase intentions. The research seeks to address the following questions: How do AI recommendations compare to influencer recommendations in a traditional e-commerce environment? Is the combination of AI and influencer recommendations more effective than AI recommendations alone? How does this combination stack up against influencer recommendations on their own? The study's findings indicate that, on conventional e-commerce platforms, the combined recommendation does not prove to be more effective than standalone AI recommendations. In fact, AI recommendations surpass this combined recommendation. However, the combination is more effective than influencer recommendations alone. Additionally, product type and consumer regulatory focus do not significantly affect the outcomes. Furthermore, for utilitarian products, the effects of influencer and combined recommendations on consumers' purchase intentions are similar. Conversely, combined recommendations are significantly more effective than influencer recommendations for hedonic products. The interaction effect between consumer regulatory focus and product type reveals that for prevention-focused consumers purchasing hedonic products, combined recommendations have a more substantial positive impact compared to influencer recommendations. In contrast, when buying utilitarian products, there is no significant difference between the two. Theoretically, this research enhances the understanding of user behavior in recommendation systems and underscores the limitations of combined recommendations. Practically, it offers insights for e-commerce platforms to refine their recommendation strategies and for online merchants to tailor their marketing strategies based on product type.

2. Literature Review

2.1 AI Recommendation Systems

Recommender systems employ AI algorithms to gather and analyze data related to customer searches, browsing, and purchases to infer consumer preferences and needs. This information helps recommend the most suitable products that meet users' needs (Xiao and Benbasat, 2007; Jansen et al., 2024). They are increasingly used to present item choice sets to customers (Mousavi et al., 2023) and assist in managing information overload arising from the vast amount of online data (Camacho et al., 2018). Existing literature mainly concentrates on two aspects. First, researchers have focused on optimizing the performance of recommendation systems to enhance the quality of recommendations. Early studies prioritized the accuracy of algorithmic recommendations (Choi and Seok, 2007; Shang and Zhang, 2009; Ye et al., 2019). Xiang et al. (2010) and Lee et al. (2014) improved the performance of algorithmic recommendation systems with real-time processing considerations. Kaminskas et al. (2017) contended that, aside from accuracy, diversity, surprise, novelty, and coverage are critical metrics for evaluating the performance of recommendation systems. Zhou et al. (2018), Feng et al. (2019), and Chen et al. (2021) utilized attention flow networks to illustrate that effective recommendation systems should account for users' attention patterns. Although existing research has improved system performance from various angles, accuracy remains the foundational basis for the widespread application of algorithmic recommendations (Leachman and Merlino, 2017; Klingbeil et al., 2024). Second, studies have examined the psychological and behavioral impacts of recommendation systems on consumers. In the context of information overload in e-commerce, personalized recommendations can save consumers' effort (Jannach et al., 2021), increase customer engagement (Kumar et al., 2019), reduce decision fatigue and purchase delays (Li and Kang, 2025), and enhance purchase intention (Li et al., 2022). For instance, it has been reported that 60% of an influencer's revenue comes from recommendations (Thompson, 2008), saving approximately $1 billion annually by reducing customer churn and increasing user engagement (Gomez-Uribe and Hunt, 2015). Basu (2021) revealed that recommendation systems are associated with a 29% increase in company revenue, and the relevance of such recommendations could potentially boost revenue by 30%. A case study by Statworx indicated that an automotive manufacturer achieved a 70% increase in conversion rates through a personalized recommendation system, directly translating to higher sales and improved customer satisfaction through relevant and useful in-car service suggestions (Statworx, 2024). Additionally, with the development of AIGC, existing research also focuses on the impact of ChatGPT recommendations on consumer choice, finding that, similar to AI recommendations, ChatGPT recommendations first affect perceived performance, followed by trust in the recommender and in the recommended product, ultimately impacting the willingness to adopt (Chang and Park, 2024).

With the rise of large-scale model technologies, consumers can engage with artificial intelligence algorithms. To receive more favorable suggestions, they may strategically manipulate the AI (Kim and Im, 2025) and intentionally let the algorithm actively understand their preferences and needs. Moreover, when consumers feel "betrayed" by artificial intelligence, they are less likely to heed its recommendations (Saenger et al., 2024). At the same time, AI recommendations can have adverse effects. Olson and Widing (2002) discovered that algorithmic recommendations can extend online consumers' decision-making time. Martin and Murphy (2017) highlighted the risks of user data leakage tied to algorithmic recommendations. Longoni et al. (2019) noted that online consumers tend to prefer human recommendations over algorithmic ones, a phenomenon known as "algorithm aversion." Additionally, AI recommendations often excessively depend on historical data, resulting in increasingly uniform outcomes, which makes users more prone to confine themselves to a limited range of product categories and create a "filter bubble" effect (Bellina et al., 2023; Areeb et al., 2023). Consequently, recommendation systems struggle to present users with a wider array of diverse or novel products that they have not previously encountered or considered (Massimo and Ricci, 2021; Mendoza and Torres, 2019; Li and Tuzhilin, 2024). Furthermore, due to issues like the cold start problem, popularity bias, and limited historical data, recommendation systems find it challenging to effectively recommend newly launched products without prior user interaction or ratings (Dhelim et al., 2021; Klimashevskaia et al., 2023).

2.2 Influencer Recommendations

The rise of social media platforms has reshaped the traditional path dependency of word-of-mouth communication, giving rise to the emerging phenomenon of the influencer economy. Social media influencers have substantial followings and serve as experts in specific content areas (Kim and Kim, 2021). They make product recommendations based on their extensive shopping experiences and specialized consumer knowledge in particular domains (Belanche et al., 2021; McKinsey, 2023). For example, an influencer might share their experience using a skincare product in an Instagram post or highlight the features of an electronic gadget in a YouTube video. According to the 2024 Influencer Marketing Report, nearly half of consumers (49%) make at least one purchase each month due to influencer posts; virtually all consumers (86%) make at least one purchase annually inspired by influencers (SproutSocial, 2024). This type of recommendation is well-received by consumers due to its authenticity and credibility, especially among younger demographics like Millennials and Generation Z (Cooley and Parks-Yancy, 2019). The market size of influencer marketing has also increased from $1.7 billion in 2017 to $24 billion by 2024 (Geyser, 2024).

Research on influencer marketing has concentrated on how influencer characteristics affect the effectiveness of recommendations. Contrary to traditional beliefs, micro-influencers (with 1,000-10,000 followers) often prove to be more effective than mega-influencers due to their high engagement rates and strong connections with their followers (Tafesse and Wood, 2021), suggesting that follower count does not guarantee marketing success (Peng and Lu, 2024). Concerning the alignment among influencers, products, and consumers, a high congruence between influencers and consumers can lead to stronger consumer-product alignment, resulting in increased consumer purchase and recommendation intentions (Belanche et al., 2021; Venciute et al., 2023). Other research examines the influence of factors such as influencer expertise (Hughes et al., 2019), attractiveness (Lou and Yuan, 2019), post features (Farivar et al., 2023), and emotional attachment (Sarkis et al., 2024) on the effectiveness of recommendations. Unlike traditional advertising, consumers often view influencer recommendations as more authentic and trustworthy, resembling the opinions of friends (Audrezet et al., 2020; Wentzell, 2021). Additionally, consumers interact with content shared by influencers through liking, commenting, and sharing, which significantly enhances brand awareness and recall (Spörl-Wang et al., 2025). Recommendations from influencers directly boost consumer engagement and purchasing, while also fostering brand loyalty (Sharma et al., 2024; Ilieva et al., 2024). Moreover, prior research has explored the importance of sponsorship disclosure in influencer marketing. When sponsorship content is not transparently disclosed, influencers might endorse products that could be harmful to consumers, misleading them through these covert advertisements, thus undermining consumer trust (Sanmiguel and Sábada, 2024). Ershov et al. (2025) discovered that 96% of sponsored posts were not disclosed and that consumers struggled to recognize sponsored content. Furthermore, influencer credibility diminishes when content is perceived as overly saturated with sponsorship (Cartwright et al., 2022).

Traditional e-commerce platforms (such as Amazon, Taobao, and JD.com) initially relied on search functions and internal recommendation systems to attract consumers. With the rise of the influencer economy, influencers have become an important bridge between consumers and e-commerce platforms, making product recommendations based on their authenticity, credibility, and broad audience base (Alcántara-Pilar et al., 2024; Libai et al., 2025). Influencer marketing is utilized in various ways on traditional e-commerce platforms, including influencer anchors in live e-commerce, influencer recommendation videos on product detail pages, and influencer recommendation prompts in product titles. The influencer marketing scenario in traditional e-commerce platforms explored in this paper aims to provide consumers with a set of products, indicating that influencers recommend all the items in the set as they search for a product that meets their needs. Unlike other scenarios, this approach does not offer specific information about the influencer but emphasizes that they suggested the product. While existing literature focuses on the role and impact of influencers in the marketing process, this paper centers on the cue “products are recommended by influencers."

2.3 Comparison and Combination of Various Recommendations

AI recommendations and influencer recommendations are two significant methods for making recommendations on e-commerce platforms, each with unique advantages and limitations. Existing literature primarily emphasizes comparisons between human experts and algorithmic recommendations. Research has shown that when participants receive financial advice from both human experts and algorithms, human recommendations tend to be more influential (Önkal et al., 2009). Human evaluations are generally more practical, fair, and flexible in employee selection processes compared to algorithm-based evaluations (Diab et al., 2011). Similarly, when it comes to joke recommendations, people prefer those from humans over algorithms (Yeomans et al., 2019). The AI recommendation of experience products may lead to greater cognitive conflict than human recommendations (Xie et al., 2022). Conversely, in specific product recommendations or contextual situations, Longoni and Cian (2022) suggest the machine word-of-mouth effect, indicating that AI recommendations can be more effective than human recommendations in the utilitarian domain, but less effective in the hedonic domain. Li et al. (2025) discovered that AI (human) recommendations can enhance purchase intentions when providing fact-based (emotional) information. Likewise, AI (human) recommendations are viewed as more effective than human recommendations for material (experiential) products (Jin and Zhang, 2025). While influencer recommendations represent a specific type of expert recommendation, they remain fundamentally a human-centric approach (Waytz and Norton, 2014).

In recent years, several studies have examined the trade-offs and integration between AI and influencer recommendations, utilizing their respective strengths. On one hand, certain research aims to enhance recommendation system performance by merging the two approaches. For instance, Chen et al. (2018) analyzed popular music data on the KKBOX platform, discovering that recommendation systems that incorporated expert attributes achieved greater accuracy and performance than those lacking expert considerations. Taneja and Arora (2018) demonstrated that multi-domain, multidimensional recommendation systems improved outcomes, reducing sparsity by 16%, alleviating the cold-start problem by 25%, increasing accuracy by 41%, and enhancing coverage by 21% compared to purely algorithmic recommendations. Weng and Zhang (2021) found that interactive systems combining algorithmic and expert recommendations significantly mitigated the cold-start issue in algorithmic recommendations. On the other hand, some studies explore the positive effects of interactions between algorithmic and expert recommendations on consumers. García-Crespo et al. (2011) used data from 10 Spanish hotels to illustrate that expert recommendation systems based on algorithms considerably improved consumer experiences. Herm-Stapelberg and Rothlauf (2020) found that combined recommendations significantly improved video clip click-through rates, user retention time, platform usage, and repeat visits. Based on product uncertainty theory, Xu et al. (2020) noted a complementary effect between algorithmic and expert recommendations. Compared to either recommendation alone, offering convergent combined recommendations to online consumers effectively lowered their perceived uncertainty.

Despite the extensive exploration of the comparison between AI recommendations and human recommendations in existing literature, research examining the combined effects of different recommendation methods (utilizing both AI and influencer recommendations) on consumer behavior remains relatively scarce. Current studies predominantly focus on the effectiveness of single recommendation types. For instance, Önkal et al. (2009) and Castelo et al. (2019) investigated the effectiveness of human expert recommendations and algorithmic recommendations in various contexts, yet systematic and comprehensive analyses are lacking regarding the combination of these two forms of recommendations. Additionally, while some studies (such as Chen et al., 2018; Taneja and Arora, 2018; Weng and Zhang, 2021) have begun to explore the integration of AI and human recommendations, they primarily focus on performance enhancement and technical applications, without delving deeply into the actual impact of combined recommendations on consumer decision-making. Therefore, this study aims to fill this theoretical gap by examining the impact of combining AI and influencer recommendations on consumer purchase intentions within a traditional e-commerce environment. By comparing the relative effectiveness of these three recommendation methods and considering variations in outcomes across different product types (utilitarian vs. hedonic) and different consumer regulatory focuses, this research offers a deeper understanding of the effects of combined recommendations.

3. Theoretical Background and Hypothesis Development

3.1 Signaling Theory

Signaling theory explains information asymmetry between buyers and sellers in a trading market (Shen, 2015), where one party can signal information to the other, reducing uncertainty and facilitating purchases or exchanges (Connelly et al., 2011). It considers how consumers make inferences based on the information provided by the seller (Moorthy and Srinivasan, 1995), treating information cues as an “information signaling mechanism” to aid decision-making (Chen et al., 2016). As consumers increasingly shop in virtual environments, distinct forms of information asymmetry create unique signals (Connelly et al., 2025). In e-commerce, signaling involves the presentation of particular website features (Mavlanova et al., 2012), and signaling theory is commonly applied to analyze website design (Shahid et al., 2024; Rosillo-Díaz et al., 2024), product marketing mix (Moon and Shugan, 2018), brand strategy (Massi et al., 2023), consumer impulse buying (Chen et al., 2019), and more.

Among recommender systems, the recommendation mechanism itself is a type of signal (Chen et al., 2019). The high degree of personalization and accuracy in AI recommendations contributes to significant homogeneity among products in the product set, which serves to inform consumers about their unique personal preferences. The fan base and socially visible attributes of influencers in influencer recommendations serve as signals to convey social trends to consumers. When multiple signals are present simultaneously, they can either work in tandem or compete with one another (Connelly et al., 2011), and the key factor is the consistency of the signals communicated by different sources. For instance, when brands convey information to consumers through omnichannel approaches, consistent signals can be established, enhancing consumers' purchase intentions and perceptions of brand authenticity (Massi et al., 2023). When recommendation sources diversify on e-commerce platforms (e.g., AI + influencer), the combination of various recommendation sources can create a holistic signal that triggers consumers' awareness of multifaceted evaluations, guiding them to focus on products from different sources and form a final candidate set. Conversely, multiple recommendation sources in a combined recommendation often convey inconsistent signals, leading to ambiguity and potentially diminishing the impact of any single signal (Paruchuri et al., 2021).

3.2 Uniqueness Theory

People often seek to set themselves apart from others (Snyder and Howard, 1980), driven by the desire to feel different and unique, thereby gaining a meaningful self-identity (Vignoles, 2000). Tian et al. (2001) defined the need for uniqueness as the desire of individuals to develop and enhance their personal and social identities through the acquisition, utilization, and disposal of consumer goods, aiming for differentiation from others. With the rise of AI tools, many studies have examined how AI contributes to shaping consumers' identities by offering tailored information and recommendations. These personalized experiences provided by AI are seen as unique (Ameen, 2021; Sands, 2022) and exclusive (Roozen et al., 2023) by consumers, ultimately enhancing their sense of personal uniqueness. Furthermore, products that are highly unique increase consumers' willingness to engage with AI services (Zaman et al., 2025), and individuals who have an independent sense of self are more likely to avoid similarities when using AI tools and are more willing to pay for AI-recommended products (Loureiro et al., 2023).

Uniqueness theory posits that when the desire to be distinct from others is triggered, and when one's self-perceived uniqueness is challenged, the urge to feel different competes with other motives aimed at preserving and enhancing that uniqueness (Snyder, 1992; Snyder and Fromkin, 1977). Recent studies reveal that using personal smartphones, which offer more privacy and personal connection than personal computers, during online shopping can heighten consumers' self-focus and shift attention toward individualized preferences, thus boosting the selection of unique products (Song and Sela, 2023). In recommender systems, when a single AI presents a set of recommended products to the consumer, the similarity and homogeneity among the products may act as personalization signals that evoke the consumer's perception of their own preferences, thereby stimulating the preservation of their uniqueness.

In the e-commerce platform, in addition to the single recommendation method, there is a combination of recommendation methods. This method involves comparing pairs of single signal sources and multiple signal sources, as well as assessing the strength of individual signal sources. Therefore, this paper utilizes signaling theory to analyze the differences between multiple signal sources and single signal sources, while applying uniqueness theory to examine the variations in signal strength among single signal sources.

3.3 Hypothesis Development

Online consumers face a significant problem of information overload. Numerous studies indicate that recommender systems can effectively assist online consumers in selecting products that better match their needs from a vast array of options (Häubl and Trifts, 2000; Senecal and Nantel, 2004; Komiak and Benbasat, 2006). Consequently, e-commerce platforms like JD.com offer online consumers a variety of recommendation methods, such as AI-driven recommendations and influencer recommendations.

Although both AI recommendations and influencer recommendations can serve as decision support tools for online consumers, there are significant differences in their essential features. AI recommendations offer decision support based on the browsing and purchasing data of online consumers and deliver highly personalized product recommendations primarily derived from the fundamental attributes of the product (Xiao and Benbasat, 2007; Benlian et al., 2012; Xu and Cenfetelli, 2014). For instance, targeted recommendations arise from analyzing attributes like the color, weight, and brightness of lamps. This method is distinguished by its high accuracy and alignment with consumer needs. According to signaling theory, AI-recommended products rely largely on consumers' private historical data; when the set of products from that single source is presented, the homogeneity among the products in the display may act as a personalization signal, triggering the consumer's perception of self-uniqueness and thereby stimulating their need for self-uniqueness protection. In contrast, influencer recommendations primarily rely on the subjective judgments of influencer users to support decision-making, suggesting products based on their personal experiences and feelings (Lyons and Henderson, 2005). For instance, an influencer might claim that a specific lamp is particularly useful for her. This method highlights variety and novelty, which means that while consumers may encounter a broader range of products, the recommendations may not align closely with their specific needs. Furthermore, while an influencer may advocate for products that align with popular trends to enhance recommendations, the influencer's mass visibility can lead to homogenized consumer choices and may signal social convergence among consumers. Previous research has indicated that AI recommendations can more accurately represent consumers' personal preferences than influencer recommendations (Yeomans et al., 2019). According to uniqueness theory, AI recommendations can stimulate the desire for consumers to distinguish themselves from others, whereas influencer recommendations may undermine consumers' self-perceived uniqueness when the need to feel different conflicts with other motivations, prompting consumers to safeguard and enhance their self-uniqueness. Therefore, we propose:

H1: Compared to influencer recommendations, online consumers have a higher purchase intention for products provided by AI recommendations.

Existing research has shown that AI recommendations often provide a result set that overlooks products that could interest consumers, leaving them in a "filter bubble" of limited diversity. In contrast, influencer recommendations can enhance recommendation quality by increasing diversity and coverage (Herm-Stapelberg and Rothlauf, 2020). As a result, e-commerce platforms like JD.com are now incorporating influencer recommendations to address the potential shortcomings of AI recommendations and increase their effectiveness. This allows consumers to view both AI and influencer-recommended products on a specific product results page. When AI and influencer recommendations are presented simultaneously, according to signaling theory, the difference between these two sources will signal consumers to engage in a more comprehensive evaluation. This means consumers recognize the need to systematically integrate information from various sources to reduce uncertainty in the decision-making process and make more informed purchase decisions.

Combined recommendations offer three advantages over single recommendations. First, they help narrow the range of products available to online consumers, reducing the need to search through multiple pages. This significantly decreases search effort and mitigates the negative effects of information overload. Second, combined recommendations enable online consumers to make purchase decisions based on various motivations, providing a deeper understanding of the recommended products and potentially lessening their uncertainty about those products. Third, they can address the limitations of AI recommendations (e.g., being limited to a single brand) and the broadness of influencer recommendations (e.g., suggesting products that don't align with consumers' needs) by offering more objective choices, thereby potentially reducing perceived risk. However, multiple recommendation sources in a combined recommendation often convey inconsistent signals, with AI recommendations signaling self-uniqueness to consumers and influencer recommendations signaling social conformity. This inconsistency can create conflicting signals and may even weaken the impact of the original single signal.

According to the uniqueness theory, the AI-recommended product set acts as a personalized signal that will evoke consumers' perception of self-uniqueness, motivating them to protect and enhance that self-uniqueness. When the influencer recommendation and the AI recommendation are presented simultaneously, the combined recommendation includes the product set suggested by the AI, which can also trigger consumers' uniqueness needs. However, the influencer recommendation on the screen conveys signals that conflict with the AI recommendation, leading to a dilution of the original personalized signal strength of the AI recommendation. Therefore, we propose:

H2: Compared to combined recommendations, online consumers have a higher purchase intention for products provided by AI recommendations.

When a single influencer recommendation is compared with a combined recommendation, the benefits of the combined recommendation as a holistic signal that prompts a thorough evaluation by the consumer become clear. When e-commerce platforms (e.g., JD.com) utilize combined recommendations to aid consumer decision-making, consumers can build a more rational and comprehensive selection of candidates from their ability to choose new and intriguing products based on influencer recommendations, as well as products that align with their interests and preferences through AI recommendations. Therefore, we propose:

H3: Compared to influencer recommendations, online consumers have a higher purchase intention for products provided by combined recommendations.

Could the impact of different recommendation methods used by e-commerce platforms be related to the type of product? In online shopping, product types are generally categorized into hedonic and utilitarian products (Hirschman and Holbrook, 1982). Hedonic products satisfy consumers' needs for sensory or emotional pleasure (Hirschman and Holbrook, 1982), such as chocolates, perfumes, and more. Utilitarian products are basic or essential items that help consumers achieve their goals or complete their tasks (Dhar and Wertenbroch, 2000), like desk lamps, computer mice, and so on. Longoni and Cian (2022) introduce the “Word-of-Machine” Effect, where the trade-off between utilitarian and hedonic attributes influences the preference for AI-based recommendations over traditional verbal recommendations or recommendations from humans. However, existing research lacks exploration of the differences between AI and human recommendations for these two types of products in e-commerce, particularly regarding combined recommendations. Therefore, we propose the following research question:

RQ1: Does product type influence the differences among AI recommendations, influencer recommendations, and combined recommendations?

Additionally, we considered consumer heterogeneity. Regulatory focus theory suggests that individuals self-regulate in response to problems (Higgins, 1997). They self-regulate based on different motivations, resulting in two types of regulatory focus: prevention-focused and promotion-focused. Promotion-focused individuals emphasize the need for enhancement, aiming at expectations and achievements, focusing on positive behavioral outcomes, aspiring for gain, and pursuing pleasure; prevention-focused individuals emphasize the need for security, aiming at responsibility and safety, focusing on negative behavioral outcomes, and avoiding pain and loss (Higgins, 1997). Promotion-focused consumers tend to use heuristic strategies to evaluate options and make decisions based on emotions, whereas prevention-focused consumers use systematic strategies to evaluate options and base their decisions primarily on the specifics of the options (Pham and Avnet, 2004; Wan et al., 2009). There are not only differences in recommendation outcomes between various recommendation methods, but also differences in how information is processed when comparing AI recommendations to influencer recommendations, as well as combined recommendations to individual recommendations. Therefore, we propose the following research question:

RQ2: Does consumer regulatory focus influence the differences among AI recommendations, influencer recommendations, and combined recommendations?

4. Research Methodology

Our experiment is primarily based on the website layout of JD.com, one of the most influential e-commerce platforms in China. JD.com has consistently used AI-driven recommendation systems to provide decision support for consumers. Following the rise of the influencer economy, it has introduced influencer recommendations while displaying the results of both AI and influencer recommendations to consumers. To test our hypotheses, we conducted three experiments. Study 1 examines the effects of individually presented AI recommendations and influencer recommendations on consumer purchase intentions. Study 2 analyzes the effects of AI recommendations presented alone and combined recommendations comprising both types on consumers' purchase intentions. Study 3 explores the effects of separate influencer recommendations and combined recommendations on consumer purchase intentions. Furthermore, all three studies aimed to investigate the potential effects of product type (hedonic vs. utilitarian) and consumer regulatory focus (promotion vs. prevention).

Before the experiments, we showed participants two 10-second animations that explained the principles behind AI and influencer recommendations to enhance their understanding. After watching the animations, participants were randomly questioned to verify their comprehension of the content. For product selection, based on previous literature and the spending habits of college students, we chose chocolate as a hedonic product and a desk lamp as a utilitarian product. Since the experiment did not involve a genuine AI simulation process, we selected the most widely recognized products: milk chocolate and a white adjustable desk lamp as the main products. All products presented to the participants were based on the actual recommendation results from JD.com. In the AI recommendation group, the participants saw the title of the recommendation source along with the set of AI-recommended products provided by JD.com when the focal product was a white adjustable desk lamp (milk chocolate), as shown in Figure 2. In the influencer recommendation group, participants saw the title of the recommendation source and the set of influencer-recommended products from JD.com when the focus product was the same, as shown in Figure 3. In the combined recommendation set, participants viewed the titles of both recommendation sources and two sets of products displayed on one page. It is important to note that influencer recommendations on JD.com do not display information about the influencer, but merely indicate that the product originated from influencer recommendations.

Figure 2: The lamps recommended by AI

Figure 3: The lamps recommended by influencer

Consistent with the study by Xiao and Benbasat (2015), to replicate real shopping scenarios as closely as possible, we mimicked the recommendation format of JD.com by presenting 12 recommended products in each instance. For combined recommendations, 6 products were recommended by AI and 6 by influencers, leading to a total of 12 products displayed to consumers. To eliminate potential confounding factors, we controlled for product price and brand. Specifically, we did not provide brand names and removed brand logos from the experimental materials. For pricing, we utilized Python software to scrape price data from JD.com for both chocolate and desk lamps, collecting a total of 5,994 chocolate price entries (M chocolate = 80.62, SD chocolate = 1.52) and 5,999 lamp price entries (M lamp = 297.14, SD lamp = 7.44). Based on the spending level of our participant group, we selected products to align with the average price of chocolate, adjusting within ±1 standard deviation of the mean, thereby maintaining all products around 80 RMB. Acknowledging the influence of sequence effects (Dou et al., 2010), we randomized the order of presentation for the two recommendation methods and the order of product appearance in all experiments.

4.1 Study1

Participants and Procedure.

The present experiment used a 2 (recommendation type: AI recommendation vs. influencer recommendation) × 2 (product type: hedonic vs. utilitarian) × 2 (regulatory focus: promotion focus vs. prevention focus) mixed experimental design. Recommendation type was implemented as a within-subjects design, while product type and regulatory focus were treated as between-subjects factors. Before the experiment, G*Power 3.1 was employed to calculate the required sample size. For a 2×2×2 mixed design with a medium effect size $f = 0.25$, $\alpha = 0.05$, four groups, and two repeated measures, a total of 64 participants were needed to achieve 90% power. A total of 107 undergraduate students (58% female; ages 18-25) participated in the experiment on site.

First, participants were randomly assigned to either the hedonic or utilitarian product groups. Second, they were shown short videos that explained the principles behind AI and influencer recommendations. Third, participants in the hedonic group were asked to imagine themselves as enthusiasts of milk chocolate, while those in the utilitarian group envisioned themselves as fans of white and upright desk lamps. Fourth, participants were presented with products recommended by both AI and influencers. They were asked to simulate an online shopping experience by selecting the product they would most likely purchase and indicating their purchase intention. Fifth, participants' regulatory focus and perceptions of product type were measured using scales, with demographic information collected (including gender, age, etc.). The purchase intention scale was adapted from items by Koufaris (2002), Karampournioti, and Wiedmann (2022), utilizing a 1–10 integer scale. The regulatory focus scale was adapted from items by Higgins (2001), Pandey, and Tripathi (2023), with all scales employing a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

Manipulation Checks.

Recommendation Type. Drawing from the measurement methods established by Benlian et al. (2012) and Zhang and Bockstedt (2020), we asked participants after the experiment: "What were the two types of recommendations provided by JD.com during this experiment?" To assess whether participants recognized the differences between AI recommendations and influencer recommendations, we utilized a 7-point Likert scale. Participants were asked to carefully consider the recommended products and respond to the following statements: "Do you think the products from the 'AI recommendations' align more with your personal preferences than the products from the 'influencer recommendations'?" and "Do you believe the products from the 'influencer recommendations' are more diverse than the products from the 'AI recommendations'?" Results indicated that 100% of participants were able to accurately identify the two types of recommendations presented in the study. Furthermore, repeated measures ANOVA results indicated significant differences in accuracy characteristics, with the AI recommendation group ($M_{AI} = 5.75$, $SD_{AI} = 0.943$) differing from the influencer recommendation group ($M_{influencer} = 2.32$, $SD_{influencer} = 1.271$) ($F(1, 106) = 459.749$, $p < 0.001$). For diversity characteristics, the AI recommendation group ($M_{AI} = 2.25$, $SD_{AI} = 0.943$) significantly differed from the influencer recommendation group ($M_{influencer} = 5.68$, $SD_{influencer} = 1.271$) ($F(1, 106) = 459.749$, $p < 0.001$), confirming the successful manipulation of recommendation types.

Product Type. We mainly adapted scales from Crowley et al. (1992) and Volz and Volgger (2022), asking participants to evaluate the utilitarian aspect of the products with items such as, "Chocolate/Lamp provides me with a lot of convenience in my life" ($\alpha = 0.904$), and the hedonic aspect of the products with items like, "Chocolate/Lamp brings me a pleasant experience" ($\alpha = 0.655$). Results from independent samples t-tests indicated significant differences in hedonic ratings between the chocolate group ($M_{hedonic} = 5.535$, $SD_{hedonic} = 0.851$) and the lamp group ($M_{hedonic} = 5.198$, $SD_{hedonic} = 0.889$) ($t(105) = 2.003$, $p = 0.048$). Additionally, utilitarian ratings also showed significant differences, with the chocolate group ($M_{utilitarian} = 4.603$, $SD_{utilitarian} = 1.111$) differing from the lamp group ($M_{utilitarian} = 6.340$, $SD_{utilitarian} = 0.722$) ($t(105) = -9.595$, $p < 0.001$), thereby validating the manipulation of product types.

Results and Discussion.

Reliability and validity test. Reliability statistics were used to analyze the reliability levels of each variable, yielding the following results: promotion-focused scale α = 0.734, prevention-focused scale α = 0.802, utilitarian product scale α = 0.904, hedonic product scale α = 0.655. An exploratory factor analysis was performed to examine the validity levels of each variable. The KMO values for all variables were above the minimum threshold of 0.5, and the results of Bartlett's test of sphericity were significant. Additionally, the variance contribution rates from the factor analysis for all variables exceeded 50%.

Main Results. An ANOVA was used to test for significant differences in online consumers' purchase intentions based on recommendation type (AI recommendations vs. influencer recommendations). The results revealed that online consumers exhibited a higher purchase intention for products provided by AI recommendations ($M_{AI} = 8.04$, $SD_{AI} = 1.654$) compared to those recommended by influencers ($M_{influencer} = 7.14$, $SD_{influencer} = 1.835$) ($F(1, 106) = 18.338$, $p < 0.001$). Therefore, H1 was supported.

Product Type. An ANOVA was used to test whether product type moderates the effect of recommendation type on online consumers' purchase intentions. The main effect of recommendation type was significant ($F(1, 105) = 18.166$, $p < 0.001$), but the interaction between recommendation type and product type was not significant ($F(1, 105) = 0.244$, $p = 0.623$), suggesting that the moderating effect of product type is not significant. To further explore the moderating effect of product type, we conducted simple effects analyses by dividing the data into hedonic and utilitarian product groups. The results indicated that for hedonic products, consumers showed a higher purchase intention for AI recommendations ($M_{AI} = 7.91$, $SD_{AI} = 1.790$) compared to influencer recommendations ($M_{influencer} = 7.11$, $SD_{influencer} = 1.565$) ($F(1, 52) = 7.072$, $p = 0.010$). Similarly, for utilitarian products, consumers exhibited a higher purchase intention for AI recommendations ($M_{AI} = 8.17$, $SD_{AI} = 1.514$) than for influencer recommendations ($M_{influencer} = 7.17$, $SD_{influencer} = 2.081$) ($F(1, 53) = 11.357$, $p = 0.001$).

Regulatory Focus. An ANOVA was used to test the moderating effect of consumers' regulatory focus. The interaction between recommendation type and regulatory focus was not significant ($F(1, 105) = 0.002$, $p = 0.961$), suggesting that the moderating effect of regulatory focus is not significant. By dividing the data into promotion focus and prevention focus groups, further analysis showed that promotion-focused consumers had a higher purchase intention for AI recommendations ($M_{AI} = 8.17$, $SD_{AI} = 1.590$) compared to influencer recommendations ($M_{influencer} = 7.28$, $SD_{influencer} = 1.885$) ($F(1, 52) = 7.596$, $p = 0.008$). Similarly, prevention-focused consumers exhibited higher purchase intentions for AI recommendations ($M_{AI} = 7.90$, $SD_{AI} = 1.699$) compared to influencer recommendations ($M_{influencer} = 6.93$, $SD_{influencer} = 1.874$) ($F(1, 53) = 11.088$, $p = 0.002$).

Discussion. The findings indicate that online consumers have a higher purchase intention for products recommended by AI compared to those recommended by influencers. The effect of recommendation type on purchase intentions is not influenced by product type; whether products are hedonic or utilitarian, consumers’ purchase intentions remain significantly higher for AI-recommended products than for those recommended by influencers. This may be due to the fact that attribute-based recommendations (such as those from AI) are more valuable to consumers, enabling them to assess the match more easily and alleviate uncertainties regarding the products (Park and Lee, 2008; Xu et al., 2020). In conclusion, this study reinforces that AI recommendations consistently surpass influencer recommendations on traditional e-commerce platforms, providing evidence of AI's effectiveness in enhancing online consumer decision-making.

4.2 Study2

Participants and Procedure.

We employed a 2 (recommendation type: AI recommendation vs. combined recommendation) × 2 (product type: hedonic vs. utilitarian) × 2 (regulatory focus: promotion vs. prevention) mixed experimental design. The recommendation type was manipulated within subjects, while product type and regulatory focus were manipulated between subjects. Before the experiment, G*Power 3.1 was used to calculate the required sample size. For a 2×2×2 mixed design with a medium effect size $f = 0.25$, $\alpha = 0.05$, four groups, and two repeated measures, a total of 64 participants were needed to achieve 90% power. A total of 88 undergraduate students (59% female; ages 18-25) participated in the experiment on site. The experimental procedures and scales used were consistent with those in Study 1.

Manipulation Checks.

Recommendation Type. Similar to the approach in Study 1, results showed that 100% of participants accurately identified the two recommendation types presented in the experiment. Repeated measures ANOVA results demonstrated significant differences in the accuracy characteristics, with the AI recommendation group ($M_{AI} = 5.37$, $SD_{AI} = 1.021$) differing from the influencer recommendation group ($M_{influencer} = 2.32$, $SD_{influencer} = 1.170$) ($F(1, 87) = 324.121$, $p < 0.001$). Similarly, for the diversity characteristics, the AI recommendation group ($M_{AI} = 2.63$, $SD_{AI} =$

1.395) exhibited significant differences compared to the influencer recommendation group ($M_{influencer} = 5.68$, $SD_{influencer} = 1.170$) ($F(1, 87) = 324.121$, $p < 0.001$), confirming the successful manipulation of recommendation types.

Product Type. Results from the independent samples t-test showed significant differences in hedonic ratings between the chocolate group ($M_{hedonic} = 5.613$, $SD_{hedonic} = 0.951$) and the lamp group ($M_{hedonic} = 5.184$, $SD_{hedonic} = 0.862$) ($t(86) = 2.182$, $p = 0.032$). Furthermore, there were significant differences in utilitarian ratings between the chocolate group ($M_{utilitarian} = 4.953$, $SD_{utilitarian} = 1.026$) and the lamp group ($M_{utilitarian} = 6.219$, $SD_{utilitarian} = 0.895$) ($t(86) = -6.055$, $p < 0.001$), confirming the successful manipulation of product types.

Results and Discussion.

Reliability and validity test. Reliability statistics were utilized to analyze the reliability levels of each variable, yielding the following results: promotion-focused scale $\alpha = 0.797$, prevention-focused scale $\alpha = 0.768$, utilitarian product scale $\alpha = 0.882$, hedonic product scale $\alpha = 0.731$. An exploratory factor analysis was conducted to examine the validity levels of each variable. The KMO values for all variables were above the minimum threshold of 0.5, and the Bartlett's test of sphericity results were significant. Additionally, the variance contribution rates from the factor analysis for all variables exceeded 50%.

Main Effects. An ANOVA was conducted to examine whether there was a significant difference in online consumers' purchase intentions between AI and combined recommendations. Results showed that there was no significant difference in purchase intentions between products recommended by AI ($M_{AI} = 7.44$, $SD_{AI} = 1.674$) and those recommended in combination ($M_{combined} = 7.67$, $SD_{combined} = 1.595$; $F(1,87) = 2.066$, $p = 0.154$). Therefore, H2 was not supported.

Product Type. An ANOVA was also conducted to test whether product type moderated the effect of recommendation type on online consumers' purchase intentions. Results showed that the interaction between recommendation type and product type was not significant ($F(1, 86) = 0.666$, $p = 0.417$), suggesting that product type has no moderating effect. Further analysis of simple effects confirmed that for hedonic products, there was no significant difference in purchase intentions between AI recommendations ($M_{AI} = 7.44$, $SD_{AI} = 1.809$) and combined recommendations ($M_{combined} = 7.78$, $SD_{combined} = 1.489$; $F(1,49) = 3.487$, $p = 0.068$). For utilitarian products, the effect of AI and combined recommendations was also not significant ($M_{AI} = 7.45$, $SD_{AI} = 1.501$; $M_{combined} = 7.53$, $SD_{combined} = 1.736$; $F(1,37) = 0.081$, $p = 0.778$).

Regulatory Focus. An ANOVA was conducted to examine the moderating effect of consumers' regulatory focus. Results showed that the main effect of regulatory focus was not significant ($F(1,86) = 0.957$, $p = 0.331$), and the interaction between recommendation type and regulatory focus was also not significant ($F(1,86) = 0.667$, $p = 0.416$), suggesting that regulatory focus did not have a moderating effect. Additionally, simple effects analysis revealed that for promotion-focused consumers, there was no significant difference in purchase intentions between AI recommendations ($M_{AI}=7.54$, $SD_{AI}=1.748$) and combined recommendations ($M_{combined} = 7.90$, $SD_{combined} = 1.700$; $F(1,40) = 2.693$, $p = 0.109$). Similarly, for prevention-focused consumers, the effects of AI recommendations ($M_{AI} = 7.36$, $SD_{AI} = 1.621$) and combined recommendations ($M_{combined} = 7.47$, $SD_{combined} = 1.487$) were also not significant ($F(1,46) = 0.226$, $p = 0.637$).

Discussion. The results indicate that there are no significant differences in the impact of AI recommendations and combined recommendations on online consumers' purchase intentions. This may be because online consumers primarily perceive uncertainty in their purchasing decisions based on product matching issues. Both AI recommendations and combined recommendations effectively address these product matching challenges. As a result, online consumers show comparable purchase intentions for products suggested by both recommendation methods. Furthermore, the moderating effect of product type did not appear to influence either the AI recommendations or the combined recommendations. This suggests that, regardless of whether the product is hedonic or utilitarian, the effectiveness of both recommendation approaches in alleviating perceived uncertainty related to product matching remains consistent, resulting in similar levels of purchase intention among consumers. In summary, the ability of both recommendation systems to effectively match products to consumer preferences plays a crucial role in shaping purchase intentions, overshadowing potential differences that might arise from the nature of the recommendation type or the product category itself.

4.3 Study3

Participants and Procedure.

We adopted a 2 (recommendation type: influencer recommendation vs. combined recommendation) × 2 (product type: hedonic vs. utilitarian) × 2 (regulatory focus: promotion vs. prevention) mixed experimental design. Recommendation type was manipulated within subjects, while product type and regulatory focus were manipulated between subjects. Before the experiment, G*Power 3.1 was utilized to calculate the required sample size. For a 2×2×2 mixed design with a medium effect size $f = 0.25$, $\alpha = 0.05$, four groups, and two repeated measures, 64 participants were needed to achieve 90% power. 91 undergraduate students (58% female; ages 18-25) participated in the experiment on site. The experimental procedure and the scales used were consistent with those in Study 1.

Manipulation Checks.

Recommendation Type. Like in Study 1, the results indicated that all participants accurately identified the two recommendation types presented in the experiment. A repeated-measures ANOVA was conducted to verify the manipulation of diversity between AI and influencer recommendations. The results showed a significant difference in perceived accuracy between the AI recommendation group ($M_{AI} = 5.37$, $SD_{AI} = 1.132$) and the influencer recommendation group ($M_{Influencer} = 2.71$, $SD_{Influencer} = 1.478$; $F(1, 90) = 134.031$, $p < 0.001$). Additionally, there was a significant difference in perceived diversity between the AI recommendation group ($M_{AI} = 2.63$, $SD_{AI} = 1.132$) and the influencer recommendation group ($M_{Influencer} = 5.29$, $SD_{Influencer} = 1.478$; $F(1,90) = 68.874$, $p < 0.001$).

Product Type. An independent-samples t-test was conducted to verify the manipulation of product type, showing a significant difference in hedonic characteristics between the chocolate group ($M_{hedonic} = 5.638$, $SD_{hedonic} = 1.042$) and the desk lamp group ($M_{hedonic} = 5.212$, $SD_{hedonic} = 0.839$; $t(89) = 2.155$, $p = 0.034$). There was also a significant difference in utilitarian characteristics between the chocolate group ($M_{utilitarian} = 4.893$, $SD_{utilitarian} = 1.043$) and the desk lamp group ($M_{utilitarian} = 5.886$, $SD_{utilitarian} = 0.898$; $t(89) = -4.852$, $p < 0.001$).

Results and Discussion.

Reliability and validity test. Reliability statistics were utilized to analyze the reliability levels of each variable, yielding the following results: promotion-focused scale $\alpha = 0.628$, prevention-focused scale $\alpha = 0.799$, utilitarian product scale $\alpha = 0.769$, hedonic product scale $\alpha = 0.750$. An exploratory factor analysis was conducted to examine the validity levels of each variable. The KMO values for all variables were above the minimum threshold of 0.5, and the Bartlett's test of sphericity results were significant. Additionally, the variance contribution rates from the factor analysis for all variables exceeded 50%.

Main Effects. An ANOVA was used to test whether there was a significant difference in online consumers' purchase intentions between influencer and combined recommendations. The results showed that purchase intention for products recommended combinedly ($M_{combined} = 8.03$, $SD_{combined} = 1.709$) was significantly higher than for products recommended by influencers ($M_{influencer} = 6.70$, $SD_{influencer} = 2.079$; $F(1,90) = 28.954$, $p < 0.001$). Therefore, H3 was supported.

Product Type. An ANOVA was conducted to examine whether product type moderated the effect of recommendation type on online consumers' purchase intentions. The results showed a significant main effect of recommendation type ($F(1,89) = 29.985$, $p < 0.001$), no significant main effect of product type ($F(1,89) = 0.033$, $p = 0.856$), and a significant interaction between recommendation type and product type ($F(1,89) = 7.383$, $p = 0.008$). The interaction effect between recommendation type and product type is shown in Figure 4, indicating a moderating effect of product type. Further simple effects analysis indicated that for hedonic products, purchase intention was significantly higher for combined recommendations ($M_{combined} = 8.32$, $SD_{combined} = 1.682$) than for influencer recommendations ($M_{influencer} = 6.36$, $SD_{influencer} = 2.345$; $F(1,46) = 34.243$, $p < 0.001$). However, for utilitarian products, there was no significant difference between combined recommendations ($M_{combined} = 7.73$, $SD_{combined} = 1.703$) and influencer recommendations ($M_{influencer} = 7.07$, $SD_{influencer} = 1.704$; $F(1,43) = 3.738$, $p = 0.060$).

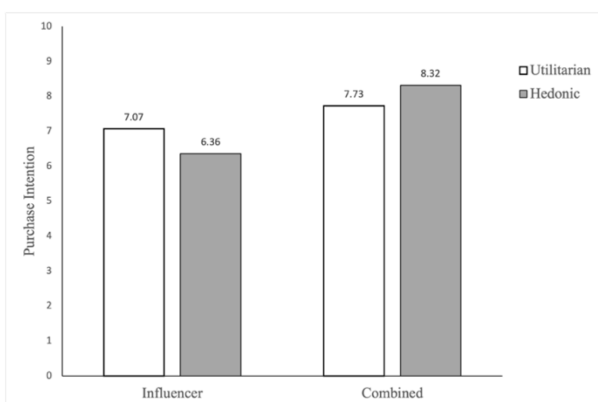

Figure 4: Interaction effect of recommendation type and product type

Regulatory Focus. An ANOVA was conducted to test the moderating effect of regulatory focus. Results showed that the main effect of regulatory focus was not significant ($F(1,89) = 1.285$, $p = 0.260$), and the interaction between recommendation type and regulatory focus was also not significant ($F(1,89) = 1.836$, $p = 0.179$), suggesting that regulatory focus did not have a significant moderating effect. Simple effects analysis showed that for promotion-focused consumers, purchase intention was significantly higher for combined recommendations ($M_{combined} = 8.02$, $SD_{combined} = 1.699$) than for influencer recommendations ($M_{influencer} = 6.36$, $SD_{influencer} = 2.327$; $F (1,44) = 28.646$, $p < 0.001$). For prevention-focused consumers, purchase intention was also significantly higher for combined recommendations ($M_{combined} = 8.04$, $SD_{combined} = 1.738$) than for influencer recommendations ($M_{influencer} = 7.04$, $SD_{influencer} = 1.763$; $F (1,45) = 6.946$, $p = 0.011$).

Three-Way ANOVA. To test whether the interaction effect of product type and regulatory focus moderates the influence of recommendation type on online consumers' purchase intentions, a three-way ANOVA was conducted with recommendation type, product type, and regulatory focus as factors. The results showed a significant main effect of recommendation type ($F (1,87) = 35.280$, $p < 0.001$), providing further support for H1. The interaction among recommendation type, product type, and regulatory focus was also significant ($F (1,87) = 4.873$, $p = 0.030$). Thus, the interaction effect of recommendation type and product type on purchase intention differs significantly between promotion-focused and prevention-focused consumers.

To further analyze the influence of consumers' regulatory focus, the data were divided into two groups: promotion-focused and prevention-focused, for separate ANOVA analyses. For promotion-focused consumers, the interaction between recommendation type and product type was not significant ($F (1,43) = 0.038$, $p = 0.847$), indicating no moderating effect of product type. For prevention-focused consumers, however, the main effect of recommendation type was significant ($F (1,44) = 11.583$, $p = 0.001$), whereas the main effect of product type was not ($F (1,44) = 0.175$, $p = 0.678$). The interaction between recommendation type and product type was significant ($F (1,44) = 10.191$, $p = 0.003$), indicating a significant moderating effect of product type. Therefore, the differences primarily stem from prevention-focused consumers.

Further simple effects analysis revealed that for promotion-focused consumers, combined recommendations had a higher impact on purchase intentions than influencer recommendations, for both utilitarian products ($M_{influencer} = 6.47$, $SD_{influencer} = 2.035$; $M_{combined} = 8.06$, $SD_{combined} = 1.298$; $F (1,16) = 11.413$, $p = 0.004$) and hedonic products ($M_{influencer} = 6.29$, $SD_{influencer} = 2.522$; $M_{combined} = 8.00$, $SD_{combined} = 1.925$; $F (1,27) = 16.868$, $p < 0.001$). For prevention-focused consumers, when purchasing utilitarian products, there was no significant difference between influencer ($M_{influencer} = 7.44$, $SD_{influencer} = 1.368$) and combined recommendations ($M_{combined} = 7.52$, $SD_{combined} = 1.909$; $F (1,26) = 0.028$, $p = 0.868$). However, when purchasing hedonic products, combined recommendations had a significantly more positive effect on purchase intentions than influencer recommendations ($M_{influencer} = 6.47$, $SD_{influencer} = 2.188$; $M_{combined} = 8.79$, $SD_{combined} = 1.134$; $F (1,18) = 17.286$, $p = 0.001$). The interaction between recommendation type and product type is shown in Figure 5 and Figure 6. Thus, for prevention-focused consumers, product type moderates the effect of recommendation type on purchase intentions. For utilitarian products, there is no significant difference, but for hedonic products, combined recommendations have a significantly greater positive impact on purchase intentions compared to influencer recommendations.

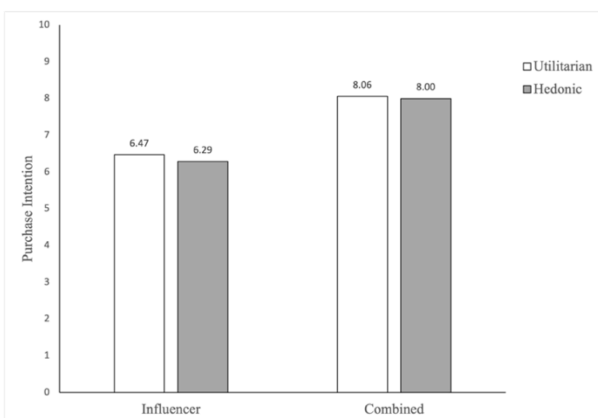

Figure 5: Interaction effect of recommendation type and product type for promotion-focused consumers

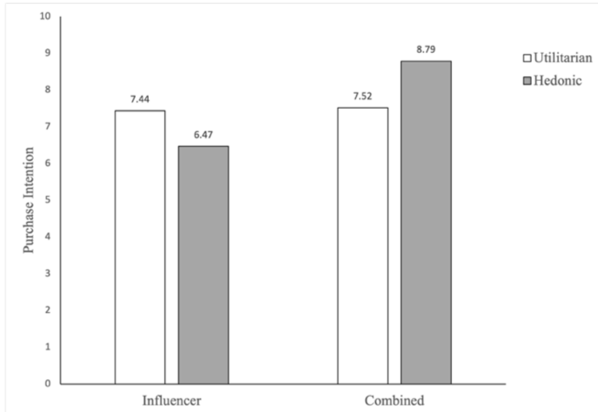

Figure 6: Interaction effect of recommendation type and product type for prevention-focused consumers

Discussion. Compared to influencer recommendations, combined recommendations lead to higher purchase intentions among online consumers. This finding is consistent with the research of Herm-Stapelberg and Rothlauf (2020), indicating that the positive impact of influencer recommendations on online consumer behavior may be less significant than previously thought. This further suggests that product matching could be a crucial factor affecting online consumers' purchase decisions. Logg et al. (2019) discovered that online consumers show greater acceptance of recommendations viewed as algorithm-based rather than expert-based. Combined recommendations integrate the benefits of AI and influencer recommendations, which may clarify why online consumers exhibit higher acceptance and purchase intentions for products recommended in combination.

The moderating effect of product type influences the impact of influencer and combined recommendations on online consumers' purchase intentions. For utilitarian products, there is no significant difference between influencer and combined recommendations; however, for hedonic products, combined recommendations have a more positive impact than influencer recommendations. This may be because the appeal of hedonic products largely depends on personal preference, leading online consumers to rely more on AI recommendations. In contrast, the appeal of utilitarian products primarily hinges on product quality, where consumers tend to prefer the support of influencer recommendations (Feick and Higie, 1992).

When considering both product type and regulatory focus as moderating factors, a significant three-way interaction effect exists among recommendation type, product type, and regulatory focus on purchase intentions. This difference is mainly observed in prevention-focused consumers. For promotion-focused consumers, product type does not influence how recommendation type affects purchase intentions. For both hedonic and utilitarian products, combined recommendations lead to significantly higher purchase intentions compared to influencer recommendations. However, there is no significant difference between influencer and combined recommendations for prevention-focused consumers when buying utilitarian products. Still, combined recommendations have a more substantial positive effect than influencer recommendations when purchasing hedonic products.

5. Discussion

5.1 Findings

This study compares the different impacts of AI recommendations, influencer recommendations, and combined recommendations on online consumers' purchase intentions. The results show that, first, there is no significant difference in purchase intentions between AI and combined recommendations, with similar outcomes observed across different product types and consumer regulatory focus. In other words, the decision by e-commerce platforms like JD.com to introduce influencer recommendations to address the potential negative issues associated with standalone AI recommendations may not have yielded the expected outcomes. The combined recommendations following the introduction of influencer recommendations show no significant differences for consumers compared to the prior results of standalone AI recommendations. Secondly, compared to products recommended by influencers, online consumers demonstrate a higher purchase intention for products recommended by AI. This trend is also evident across various product types and consumer regulatory focus. This indicates that the advantages of AI recommendations remain strong in traditional e-commerce platforms, as consumers are primarily concerned about whether the recommended results align with their own needs and preferences. Thirdly, compared to products recommended by influencers, online consumers show a higher purchase intention for combined-recommended products. At the same time, there is a moderating effect based on product types. Specifically, for utilitarian products, there is no significant difference in influencer and combined recommendations regarding online consumers' purchase intentions. However, combined recommendations have a more positive impact on online consumers' purchase intentions for hedonic products compared to influencer recommendations. The three-factor ANOVA results based on consumer regulatory focus indicate that, for promotion-focused consumers, regardless of whether the products are hedonic or utilitarian, online consumers' purchase intentions for products recommended through combinations are significantly higher than those for influencer-recommended products. However, for prevention-focused consumers, there is no significant difference between influencer and combined recommendations when purchasing utilitarian products. For hedonic products, combined recommendations exert a more positive influence on purchase intentions than influencer recommendations.

5.2 Theoretical Contributions

This study makes a theoretical contribution to the literature on signaling theory. While traditional signaling theory focuses on single signals such as price, brand, or certification, this study examines the recommender system itself as a new type of signal. Different recommendation methods can convey varying signal connotations; for instance, AI recommendations highlight consumers' uniqueness through personalized data to deliver the message of “accurately matching personal preferences,” while influencer recommendations signal “popular trends” through public visibility. Combined recommendations first convey the signal of “comprehensive assessment of needs” through the simultaneous presentation of both recommendation sources, then overlap the different signals from AI and influencer recommendations. The study's results show that AI recommendations consistently outperform influencer recommendations, indicating that during the e-commerce shopping process, consumers perceive the signal strength or type conveyed by AI recommendations as more significant than that from influencer recommendations. Moreover, there is no significant difference between AI recommendations and combined recommendations, suggesting that the uniqueness signal conveyed by AI recommendations is stable; the impact of signal conflict arising from inconsistent information is extremely weak, even when influencer recommendations are introduced.

Additionally, this study enhances the literature on uniqueness theory. While traditional uniqueness theory suggests that consumers resist following the crowd by opting for niche products, this study reveals that highly personalized AI recommendations can encourage purchases by fulfilling uniqueness needs. Consumers do not need to actively pursue differentiation when the recommendation system effectively identifies their individual preferences, instead achieving uniqueness recognition through the “customized product set” provided by the system. Previous research indicates that consumers' need for uniqueness across different contexts leads to varying preferences for artificial services or AI. In healthcare, consumers perceive AI (as opposed to humans) as more challenging in conveying patients' unique characteristics and situations, raising concerns about uniqueness neglect and resulting in resistance to healthcare AI (Longoni et al., 2019). In the social e-commerce realm, AI influencers can fulfill a role similar to that of human influencers, and when consumer demand for uniqueness is high, AI can have a more significant positive impact (Sands et al., 2022). This study found that on traditional e-commerce platforms, AI recommendations can trigger the protection of one's uniqueness compared to those from humans, leading consumers to favor AI recommendations more, and this need for uniqueness is not easily influenced by other motives.

Finally, this study also makes contribution to the literature on regulatory focus theory. Theoretically, promotion-focused consumers should be more prone to the affective (influencer) path, while prevention-focused consumers should depend more on the rational (AI) path. However, in the context of combined recommendations, both AI and influencer recommendations seem to satisfy the dual needs of promotion (ideal pursuit) and prevention (risk aversion). The results indicate that regulatory focus did not display a moderating effect when comparing the two recommendation approaches. This may be attributed to the presence of explicit shopping goals in the consumer's decision-making process, where the significance of inherent product attributes surpasses the credibility of the recommendation source, resulting in a functional need that diminishes the difference in regulatory focus.

5.3 Managerial Implications

This study offers valuable insights for e-commerce platforms and online merchants. For e-commerce platforms, recognizing the strong influence of AI recommendations on consumer purchase decisions is crucial, and optimizing the effectiveness of these AI recommendations should be a priority. Our findings show that online consumers exhibit higher purchase intentions for products recommended by AI compared to those recommended by influencers. This indicates that despite the emergence of new recommendation methods, such as influencer recommendations, AI continues to be the most impactful approach for shaping consumers' online shopping behavior. Furthermore, platform managers should encourage online merchants who rely on influencer recommendations to adopt combined recommendations as a more effective support tool for consumer decision-making. Our results illustrate that combined recommendations result in higher purchase intentions than influencer recommendations. Finally, it is important to note that combined recommendations are not always the most cost-effective option; when the platform's algorithms effectively provide personalized recommendations, further investment in influencer recommendations may be unnecessary.

For online merchants, prominently displaying AI-recommended products on product pages is advisable, as our study confirms the positive impact of AI recommendations on consumer purchase decisions. Additionally, merchants should consider using combined recommendations instead of relying solely on influencer recommendations. These combined recommendations can help consumers create a more rational selection of options, potentially reducing their perceived uncertainty. Our findings show that consumers have higher purchase intentions for products recommended through a combination of approaches than for those recommended solely by influencers. Finally, enhancing membership management can aid online merchants in identifying consumers' regulatory focus more effectively and in selecting suitable product types for their recommendation strategies. For example, for promotion-focused consumers, combined recommendations may support decision-making, while for prevention-focused consumers, combined recommendations may work best when recommending hedonic products, whereas influencer recommendations might be preferred for utilitarian products, especially when operating with limited budgets or resources.

5.4 Research Limitations and Future Directions

This study has certain limitations. First, the context of influencer recommendations in this study is limited to page prompts on e-commerce platforms. Future research could explore the cross-platform effects of influencer recommendations on product sales across social media platforms. Second, the combined recommendation examined in this research focuses on the joint presentation of AI and influencer recommendations on e-commerce platforms. Future studies could investigate the effects of various combinations of different recommendation methods on consumer behavior. Third, this study simulates the recommendation system on the JD.com platform. Future research could consider conducting field experiments based on real-world scenarios on JD.com to further validate and explore the findings. Fourth, while it compares the effects of AI, influencer, and combined recommendations on online consumers' purchase intentions, future research could delve into the psychological mechanisms underlying the impact of different recommendation types on online consumer decision-making. This is especially relevant regarding issues such as privacy concerns, algorithm aversion, consumer trust, and the interpretability and reliability of recommendation results. Additionally, this study primarily examines the influence of different recommendation types on purchase intentions without addressing consumers' browsing behaviors. Online consumer decision-making typically involves two stages: browsing and purchasing. Existing literature has found that different recommendation methods have varying effects across these stages (Liang et al., 2006; Zhang & Bockstedt, 2020). Future research could investigate how various recommendation methods affect browsing behavior, allowing for a more comprehensive comparison of their effects across both browsing and purchasing stages.

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APPENDIX

Measurement Items

Construct	Items	Measurement	Supporting Literature
Purchase Intention	PI	If your budget is sufficient, what is your purchase intention of this chocolate (table lamp) recommended by AI(Daren/Combined)?	Koufaris (2002); Karampournioti and Wiedmann (2022)
Promotion-Focused	ProF1	Compared to most people, how often do you find it harder to achieve your goals?	Higgins et al. (2001); Pandey and Tripathi (2023)
	ProF2	How often do you strive harder out of a desire for success?	
	ProF3	How often do you fully achieve what you set out to accomplish?	
	ProF4	I notice that my performance falls short of my expectations at key moments.	
	ProF5	I feel my life is getting better.	
	ProF6	I rarely have hobbies or activities that interest me.	
Prevention-Focused	PreF1	How often did you do things your parents could not tolerate while growing up?	Higgins et al. (2001); Pandey and Tripathi (2023)
	PreF2	How often did you upset your parents while growing up?	
	PreF3	How often do you adhere to the rules set by your parents?	
	PreF4	How often did you exhibit behavior your parents disliked while growing up?	
Utilitarian	Uti1	Chocolate/lamps can bring a lot of convenience to my life.	Crowley et al. (1992); Volz and Volgger (2022)
	Uti2	Chocolate/lamps is useful to me.	
	Uti3	Chocolate/lamps is worth buying.	
Hedonic	Hed1	Chocolate/lamps can bring me a pleasant experience.	Crowley et al. (1992); Volz and Volgger (2022)
	Hed2	Chocolate/lamps can improve my enjoyment of life.	
	Hed3	The design and style of the chocolate/lamps are very attractive.	