HOW DOES ARTIFICIAL INTELLIGENCE MAKE THE WORLD A BETTER PLACE? UNPACKING THE EFFECTS OF ARTIFICIAL INTELLIGENCE RECOMMENDATIONS OF SOCIAL GOODS ON E-COMMERCE WEBSITES

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ABSTRACT

In the current e-commerce marketing environment, artificial intelligence (AI) recommendation systems are widely used in various business scenarios, but little attention has been given to their application to social goods. On the basis of the persuasion knowledge model and goal framing theory, this study explores the mechanism of the recommendation approach (AI vs. human) in promoting consumer purchase behavior related to social goods. Three experiments are conducted, which show that AI recommendations have significant advantages in increasing consumers' intention to purchase social goods on e-commerce platforms. Specifically, perceived manipulative intention serves as a mediator between the recommendation approach (AI vs. human) and consumers' purchase intentions. Additionally, goal framing moderates the effects of the recommendation approach on consumers' purchase intentions: consumers respond more positively to AI recommendations under loss framing, whereas human recommendations have greater persuasive power under gain framing. This study expands the application scenarios of AI recommendation in the field of social marketing and enriches the theoretical explanatory power of persuasion knowledge models in the promotion of social goods via e-commerce.

Keywords: AI recommendation; Perceived manipulative intention; Goal framing; Purchase intention

1. Introduction

The rise of artificial intelligence (AI) is reshaping strategies, activities, interactions and relationships across industries; one of the greatest strengths of AI is its ability to acquire information and solve problems via deep learning, knowledge creation and transfer and make predictions owing to its computational power, which is based on statistical models (Dwivedi et al., 2021; Asante and Jiang, 2023; Sullivan and Fosso Wamba, 2024). This transformation is

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Cite: Zhou, F., Liang, Z., Zhang, N., & Mou, J. (2026, May). How does artificial intelligence make the world a better place? Unpacking the effects of artificial intelligence recommendations of social goods on e-commerce websites. *Journal of Electronic Commerce Research, 27*(2).

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particularly salient in the domain of social marketing, aligns corporate goals with social welfare through socially beneficial activities (Varadarajan and Menon, 1988; Simpson et al., 2021). In this context, social goods (such as charity-related products or eco-certification programs) have a clear twofold nature: while functioning as market goods, they incorporate measurable social value, with a portion of the proceeds directly supporting designated charity projects (Simpson et al., 2021).

Typical examples include charity-branded goods where sales fund education programs, eco-certified appliances that reduce environmental pollution, and fair-trade commodities that support ethical labor practices. Unlike ordinary products, social goods inherently integrate moral and emotional appeals, as consumers perceive their purchasing behavior as contributing to do good deeds (Hermann, 2022). Consumers' purchasing decisions for these goods constitute prosocial behavior, reflecting voluntary actions aimed at benefiting others through economic choices (Simpson et al., 2021). With the popularization of companies leveraging corporate social responsibility (CSR) activities as a strategic tool in brand management (Simpson et al., 2021), consumers' awareness of CSR is rapidly increasing (Rayne et al., 2020), and buying social goods on e-commerce platforms has become an extremely convenient way to support enterprises' CSR (Chen et al., 2023; Suryavanshi et al., 2024). Consequently, A large number of enterprises are using AI to help design social goods related projects and persuade consumers to participate, but the academic research is still very scarce. However, the effectiveness of AI recommendations in this specific context presents a significant practical challenge: while human recommendations have the opposite characteristics for matching preferences (Babatunde et al., 2024), social goods uniquely activate consumers' moral reasoning systems (Hermann, 2022), making dimensions like transparency (where AI is often perceived as lacking) and source credibility (where humans may excel) critically important determinants of persuasion success. This tension creates uncertainty regarding the optimal deployment of AI versus human agents for recommending social goods on e-commerce platforms.

Guided by the Persuasion knowledge model (PKM, Friestad and Wright, 1994), we seek to explain this challenge. PKM provides a solid theoretical basis for revealing the fundamental differences in consumers' persuasion knowledge activation patterns between contexts involving algorithmic agents and human agents (Kim and Kim, 2013). AI recommendation has been commonly used for personal and business purposes, such as intelligent assistants, music, financial planning, process automation, and credit scoring, presenting fundamentally different persuasion mechanisms compared with human recommendations because of its algorithmic transparency and absence of social–emotional cues (Chintalapati et al., 2022). However, in the context of social goods, this difference is amplified. Specifically, AI recommendations may reduce cognitive monitoring due to their perceived objectivity (Wien and Peluso, 2021), whereas human recommendations heighten suspicion through interpersonal inference processes (Hsieh, 2023). This process is further complicated when AI is regarded as a corporate tool, substituting for human agents traditionally presumed to possess autonomous motives, thereby disrupting conventional PKM assumptions (Song et al., 2021). Moreover, consumers evaluating social goods face a dual framework balancing moral legitimacy (sensitive to manipulative intent) and utilitarian value (responsive to personalization) (Huang and Rust, 2024), intensifying the PKM dynamics. To resolve this dilemma, we draw upon goal framing theory (Levin et al., 1998; Jain and Rathi, 2023). This theory suggests that loss-framed messages (emphasizing preventing negative outcomes, e.g., "Without your support, 100 children will lose access to education") may mitigate scrutiny of AI's transparency deficits by focusing attention on societal urgency (Riefler et al., 2024). In contrast, gain-framed messages (highlighting positive outcomes, e.g., "Your purchase empowers 100 children with education") leverage emotional resonance, potentially aligning with the perceived sincerity advantages of human recommenders (You and Liu, 2024). Thus, goal framing offers a theoretical pathway to potentially enhance the effectiveness of either recommendation source in the social goods context.

The theoretical insights from PKM and goal framing theory illuminate the unique challenges of recommending social goods, yet three critical limitations persist in the extant literature. First, current research focuses on consumers' responses and preferences related to human or AI recommendations (Jin and Zhang, 2023; Yang et al., 2024), mostly exploring their application in generalized scenarios, such as exploring consumers' intentions to adopt AI recommendations for utilitarian and hedonic product types (Longoni and Cian, 2022), neglecting social goods' unique dual-goal conflict. While AI excels at matching individual preferences through data-driven personalization (Babatunde et al., 2024), its application to social goods triggers unique psychological processes, as these products inherently activate consumers' moral reasoning systems, making recommendation transparency and source credibility critical determinants of persuasion success (Hermann, 2022). Second, despite PKM' s theoretical emphasis on perceived manipulative intent as a core mediator in persuasion episodes (Friestad and Wright, 1994), empirical validation of its mediating role specifically linking recommendation source (AI vs. human) to social goods purchase decisions remains absent. This gap is further accentuated by evidence that AI's perceived identity as a corporate tool disrupts traditional PKM assumptions about agent autonomy (Song et al., 2021), suggesting a potentially unique mediational pathway requiring direct testing. Third, although Goal Framing Theory offers a compelling rationale for how message framing (loss vs. gain) could strategically compensate for or augment source-specific limitations (Levin et al., 1998; Riefler et al., 2024; You and Liu, 2024), the critical interaction between recommendation source and message framing remains entirely unexplored in the social goods domain.

All in all, building upon the PKM and goal framing theory, this research aims to address the following pivotal question: Under what conditions, and through what mechanisms, do AI versus human recommendations on e-commerce platforms effectively influence consumers' purchase intentions for social goods, considering the critical roles of perceived manipulative intent and message framing (loss vs. gain)? Through three scenario experiments, this research examines the impact of the recommendation approach (AI vs. human) on consumers' purchase intentions for social goods on e-commerce platforms and explores the moderation effect of goal framing. On the basis of the PKM, this study deepens the understanding of the recommendation approach (AI vs. human) in the field of prosocial marketing by analyzing the role of perceived manipulative intention and goal framing between different recommendation approaches on consumers' prosocial purchase intentions (Hermann, 2022). Our conclusions also provide practical suggestions for enterprises on how to choose a recommendation approach to promote social goods.

2. Literature Review

2.1. AI Recommendation vs. Human Recommendation in the Social Goods Context

AI recommendation is based on the data processing and reasoning ability of AI to instantly recommend products to users by collecting and processing relevant information about a product, a user, and the interaction between the user and the product and generating personalized predictions of the user's preferences about the product or service (Tarus et al., 2018; Gupta et al., 2022). AI recommendation systems are widely used in profit-driven scenarios, such as e-commerce and streaming platforms (Sullivan and Fosso Wamba, 2024). Their data-driven precision can reduce consumers' search costs (Bawack et al., 2022), increase product browsing volume and conversion rates (Lee and Hosanagar, 2020), and enhance decision-making efficiency (Huang and Rust, 2021). However, existing studies focus predominantly on AI recommendations for for-profit products (Tarus et al., 2018; Jin and Zhang, 2023), while their application to social goods remains underexplored. Social goods are products sold through social marketing, i.e., companies donate to charity-related project that linking consumer purchasing behavior with donations that benefit charitable goals, which can achieve a win–win situation for public welfare and companies (Varadarajan and Menon, 1988). Social goods differ fundamentally from ordinary commodities because of their embedded ethical attributes (Schamp et al., 2019) and reliance on consumers' prosocial motivations. This distinction raises critical questions regarding the comparative efficacy of AI versus human recommendations in optimizing utilitarian value through data-driven mechanisms.

Human recommendation is based on an expert, such as a salesperson expert, such as human-led customer service on e-commerce platforms such as Amazon and Taobao.com, or it can act as a third-party role, such as a relative, a friend, or a stranger who shares a positive purchase and usage experience on social media (Deng et al., 2019). In this paper, we focus on the former type and define a human recommendation as a recommendation from an expert who provides product recommendation services online. AI and human recommendations differ fundamentally in five dimensions crucial to persuasive outcomes: tangibility, transparency, recommendation logic, mental capacity, and emotional ability. Table 1 summarizes the key distinctions between AI and human recommendations across these five dimensions.

The comparative analysis presented in Table1 underscores the profound differences between AI and human recommenders. These distinctions have significant and often contrasting implications for persuasive effectiveness, particularly concerning social goods where factors like trust, authenticity, moral accountability, and emotional resonance are paramount. For instance, while AI excels in managing information complexity through rational, data-driven logic (Longoni and Cian, 2020), its inherent intangibility (Cheng et al., 2022) and lack of transparency (Hamby and Brinberg, 2018; Jago, 2019) pose challenges for building trust, especially on moral issues. Conversely, the physical presence and explainability of humans foster ethical authenticity and trust. Furthermore, the attribution of mental capacity and intention fundamentally alters how responsibility for persuasive tactics is perceived (Bauer et al., 2023; Garvey et al., 2023). Perhaps most critically for social goods, the differential emotional ability highlights AI's current deficit in leveraging affective dimensions and empathetic connection (Bonezzi and Ostinelli, 2021; Longoni and Cian, 2022), a domain where humans possess a distinct advantage through strategies like storytelling that mitigate perceptions of manipulation (Kang et al., 2022) and convey the emotional authenticity essential for altruistic motivation (Schamp et al., 2019). These core differences set the stage for understanding the divergent persuasive pathways explored in the subsequent hypotheses.

Table 1. Key Differences Between AI and Human Recommendations

Dimension	AI recommendation	Human recommendation	Key Implications for Persuasion (especially Social Goods)
Tangibility	Embedded in apps, low visibility, intangible (Cheng et al., 2022)	Physical presence (e.g., live representatives).	AI's intangibility may erode trust for moral accountability; human presence enhances perceived ethical authenticity (Varadarajan and Menon, 1988; Cheng et al., 2022)
Transparency	Complex reasoning opaque ("black box operation"), difficult to understand, explain, verify (Jago, 2019)	Interpretable; experts can explain logic in real-time.	Lack of transparency exacerbates skepticism, particularly for moral claims; human explainability builds trust (Hamby and Brinberg, 2018; Jago, 2019)
Logical mechanism	Based on behavioral tracking and data analysis; filters information, reduces overload. Emphasizes factual, rational, logical, holistic assessment (Longoni and Cian, 2020)	N/A (While humans can use logic, the core contrast here is AI's unique strength in data-driven, rational filtering. Human logic often integrates other dimensions like emotion/experience)	AI improves decision quality by managing information complexity through rational criteria (Longoni and Cian, 2020) (Note: This dimension highlights AI's unique strength)
Mental capacity	Monitored/manipulated machine; perceived as lacking consciousness/intention (Garvey et al., 2023)	Intentional agent; capable of forming intentions (Bauer et al., 2023)	Responsibility attribution shifts: manipulative strategies may be attributed to the company behind AI, not AI itself; humans are evaluated on their work's value (Bauer et al., 2023; Garvey et al., 2023)
Emotional ability	Lacks sensory/emotional capacity; relies on rational data patterns. (Bonezzi and Ostinelli, 2021; Longoni and Cian, 2022)	Grounded in sensory experience, emotion, intuition, affective evaluation (Wien and Peluso, 2021; Longoni and Cian, 2022)	Human ability enables empathetic storytelling, reducing perceived manipulative intent; crucial for conveying emotional authenticity required in altruistic contexts (Schamp et al., 2019; Bonezzi and Ostinelli, 2021; Kang et al., 2022; Longoni and Cian, 2022)

These contrasts take on new significance in the context of social goods. Previous research has focused on profit-driven scenarios where AI efficiency outweighs transparency concerns (Lee and Hosanagar, 2020). However, for social goods, ethical attributes such as charitable relationships amplify scrutiny of manipulative intent (Song et al., 2021), turning AI's lack of emotional capacity and intentionality into a double-edged sword. The operational advantages of AI recommendations may become liabilities in the context of social goods, where consumers demand emotional consistency and moral responsibility, posing a paradox that remains unresolved in the literature.

2.2. Persuasion Knowledge Model and Perceived Manipulative Intention

The persuasion knowledge model (PKM; Friestad and Wright, 1994) reveals how consumers identify, interpret, and respond to marketing persuasion behaviours, providing an important perspective for understanding consumers' reactions to recommendations (Campbell, 1995; Eisend and Tarrahi, 2022). Its core proposition holds that consumers gradually develop persuasion knowledge through market interactions—a dynamic cognitive system about marketing strategies, the motives of persuaders, and coping techniques. A core component of PKM is perceived manipulative intent (PMI), which refers to the belief held by an individual that a suggestion is intended to covertly influence one's own behavior through deceptive tactics (Campbell, 1995). Consumers accumulate knowledge about the persuasive tactics that marketers use to deliver their messages, and consumers then use this persuasion knowledge to interpret, evaluate, respond to and make inferences about persuasion attempts (Eisend and Tarrahi, 2022). As consumers accumulate persuasion knowledge, they can use it more effectively to assess the manipulative nature of marketers' messages. If consumers perceive manipulativeness when processing a message, they resist the persuasion embedded in the message. Thus, the degree to which consumers' persuasion knowledge is activated depends on the degree to which the merchant's manipulative intent is perceived as significant.

In this research, AI recommendations is considered could trigger persuasion knowledge activation in two aspects: the algorithmic opacity of AI intensifies suspicion (Garvey et al., 2023) and the lack of emotional agency of AI undermines trust in prosocial settings (Bonezzi and Ostinelli, 2021). In the case of for-profit AI recommendations, persuasion knowledge activation is often mitigated by perceived utilitarian benefits (e.g., convenience, Lee and Hosanagar, 2020). However, the ethical salience of social goods increases persuasion knowledge sensitivity: consumers view AI recommendations as potential tools for "cause exploitation" (Song et al., 2021), especially when algorithmic opacity obscures the link between purchases and social impacts (Varadarajan and Menon, 1988). Extant research has revealed paradoxical persuasion knowledge dynamics in the context of AI. Specifically, although the nonhuman agency of AI reduces the direct attribution of manipulative intentions (Dattathrani and De', 2023), its lack of transparency fuels speculation about companies' hidden agendas. For example, Kang et al. (2022) reported that the use of AI-driven charitable advertisements featuring emotional cues (such as sad emojis) backfires by triggering persuasion knowledge activation, which is different from human recommendations that mitigate distrust through real-time interpretation (Deng et al., 2019).

Many studies have explored the factors influencing manipulative intent inference, and contextual cues are important for triggering manipulative intent inference. For instance, Wen et al., (2020) combined cognitive load theory and the PKM to investigate the interaction effect of cognitive load and disclosure language on the activation of persuasion knowledge and the perceived manipulativeness of native advertisements. They reported that when people have more cognitive resources, the effect of disclosure language becomes more prominent because explicit labelling triggers stronger conceptual persuasion knowledge and perceived manipulativeness. Similarly, the framing of CSR messages affects the degree of manipulativeness that consumers perceive in these messages. Prevention-focused messages are more likely to activate persuasion knowledge than promotion-focused messages are, and consumers thus tend to perceive the former as manipulative or deceptive (Lee et al., 2020). Beyond advertising, service contexts also matter: Liu et al., (2019) suggested that when service providers are frequently approached and enthusiastically provide irrelevant information, consumers perceive highly attentive service as their persuasive strategy and suspect that they have self-interested motives. Conversely, individuals exhibit less skepticism of manipulative intent when they perceive targeted political advertisements as matching their party preferences and issue interests (Hirsch et al., 2024). The presence of baseline disclosures interacts with elaboration motives, which in turn affects product evaluations.

Previous research has focused on the negative impact of manipulative intent inferences on consumer behavior and attitudes. Consumers' knowledge of public welfare marketing campaigns plays an important role in determining their evaluation of public welfare marketing campaigns and their attitudes towards for-profit companies. Savvy consumers' persuasion knowledge of public welfare marketing campaigns leads them to recognize that public welfare marketing campaigns are not corporate philanthropy but rather strategic marketing tools. Inevitably, these consumers perceive the manipulative intent of corporate public welfare marketing campaigns (Hamby and Brinberg, 2018). Compared with the use of happy and neutral emoji images, the use of sad emoji images in charity advertisements leads consumers to infer manipulative intent on the part of the organization, which in turn reduces donations (Kang et al., 2022). Manipulative intent activates consumers' skepticism and resistance to public service marketing campaigns, considering that one of the main purposes of corporate public service marketing campaigns is to engage consumers by highlighting a brand's CSR efforts (Song et al., 2021). Highlighting manipulative intent reduces the effectiveness of narrative advertising persuasion and increases the likelihood of emotional resistance. Providing sponsor disclosure significantly reduces the inference of manipulative intent when viewers approve of the advertisement, which in turn leads to positive attitudinal and behavioural outcomes (An and Ha, 2023). In the context of tourism, destinations acquire location data by tracking tourists' cell phones and even encouraging them to connect in exchange for personal data; thus, tourists who suspect manipulative intent in the implementation of wireless tracking technologies can develop negative attitudes towards wireless technologies and destinations (Lee et al., 2024).

However, in the scenario of AI recommendations for social goods, the effect of perceived manipulative intention will make a big difference. First, there is a difference in the mechanism of intent attribution. When the recommending entity is AI, consumers' criteria for determining "manipulative intent" undergo a fundamental transformation. In the absence of the baseline information needed to explain relative differences, individuals infer greater manipulative intent, which activates persuasion knowledge and negatively affects product evaluations. When influencers share information, high-arousal language may lead consumers to perceive intentions as manipulative, leading to distrust and reduced engagement (Cascio Rizzo et al., 2024). Thus, even when the same persuasive strategy is used, the perceived intensity of manipulative intent triggered by AI recommendations may be significantly weaker than that triggered by human recommendations. Second, there is an interaction effect between ethical attributes and algorithmic logic. Social goods possess both commercial and moral attributes (Schamp et al., 2019), and this duality leads consumers to adopt more complex criteria for activating persuasion knowledge. Previous research has shown that when human recommenders use public welfare-related strategies, consumers will increase their standards for moral scrutiny (Hamby and Brinberg, 2018). However, owing to the lack of emotional expression ability of AI systems (Bonezzi and Ostinelli, 2021), they may not be able to effectively convey moral sincerity. Instead, it may trigger the "hypocrite paradox"; that is, the more an AI recommendation emphasizes social benefits, the more likely it is to be regarded as manipulative behavior that uses the guise of public welfare. In short, compared with humans, the perceived lack of intentionality in AI (Garvey et al., 2023) may reduce the attribution of direct manipulation intent, but its corporate associations and emotional neutrality create new avenues for the activation of perceiving manipulative intent (Bauer et al., 2023).

These contradictory findings reveal a crucial research gap concerning the activation mechanisms of persuasion knowledge in social goods contexts where AI functions as an unintentional actor. Notably, existing PKM research focuses on human persuaders or traditional advertising forms (Hamby and Brinberg, 2018; Kang et al., 2022), resulting in limited understanding of how AI-driven recommendations interact with persuasion knowledge in social goods consumption.

2.3. Goal Framing

The message framing effect refers to the adoption of different strategies to present information, which results in the receivers of information making different decision-making judgements about the same information (Kim and Sung, 2013). While traditional framing research predominantly examines human-generated messages, emerging evidence suggests that AI systems may elicit distinct responses because of their perceived objectivity (Longoni et al., 2019). Goal framing can be divided into gain framing and loss framing, as proposed by Levin et al. (1998). It is a type of framing effect that emphasizes that two types of goal framing could produce different persuasive effects even though they mean the same thing. This distinction is particularly relevant for social goods consumption, where purchase decisions often involve ethical trade-offs between self-interest and collective welfare (Hermann, 2022). When a message is framed in terms of gain framing, it emphasizes the positive benefits that can be obtained by purchasing a certain product or service, whereas when a message is framed in terms of loss framing, it emphasizes the negative consequences of not purchasing a certain product or service. Both gain framing and loss framing facilitate consumer actions. For example, in the case of consumers' intention to use environmentally friendly products, Moon et al. (2016) reported that loss framing, which emphasizes the negative environmental consequences of nonapplication, promotes consumers' use of environmentally friendly products more than gain framing does. Moreover, in terms of the impact of message framing on physical activity, Kyung et al. (2024) reported that, compared with neutral messages, both gain framing and loss framing significantly increase users' likelihood of achieving exercise goals and improve goal completion rates.

3. Research Hypotheses

3.1. The Impact of the Recommendation Approach on the Effectiveness of Social Goods

The purpose of AI and human recommendation is to persuade consumers about online marketing to achieve marketing goals related to product purchases and ad clicks. PKM was used to explain how consumers discern persuasive intent in different recommendation sources—a critical mechanism in comparing AI and human agents (Jago, 2019). According to the PKM, when faced with public welfare product recommendation scenarios, users are not passive recipients of information but instead have the ability to use their existing persuasion knowledge to respond to the recommender's persuasion and orientation (Friestad and Wright, 1994). After being activated and applying persuasion knowledge, users generally become skeptical of the recommended information, which reduces their intention to adopt the recommended information and creates strong persuasive resistance, triggering a negative consumer response (Kim et al., 2021). Certain preconditions are needed to activate persuasion knowledge, and this paper hypothesizes that different recommendation methods stimulate different levels of persuasion knowledge in consumers, thus affecting their choice and purchase of social goods. Specifically, persuasion attempts are evaluated through two dimensions: the salience of persuasive motivation and the perceived ability to intentionally manipulate. There are great differences between these dimensions in AI and human recommenders, as described below.

AI's perceived lack of human-like consciousness (Bigman and Gray, 2018) and commercial intent (Kim and Duhachek, 2020) reduces motive salience, whereas human recommenders inherently signal stronger persuasive intent because of their perceived self-interest (Karagür et al., 2022). According to the PKM, the salience of persuasive motivation influences consumers' responses, and the more salient the persuasive motivation of an advertisement is, the more likely it is to lead a consumer to activate persuasion knowledge, which in turn leads to negative emotions and attitudes, such as resistance to the persuasive attempts of the recommender. Consumers have less persuasion knowledge that is relevant to AI because AI recommendations have low interpretability, meaning that it is difficult for users to understand the mechanisms by which AI operates and even more difficult for them to perceive and suspect persuasive AI motives (Jago, 2019). Since human experts' sales results are closely related to private interests, consumers are prone to recognize the obvious persuasive motives of human experts to make profits by persuading consumers to buy, which may increase their persuasion knowledge and adoption of evasive strategies. These strategies are manifested in specific behaviors, i.e., lowering the intention to accept the recommended information and the evaluations of the recommenders. Moreover, consumers are more likely to view human experts as recommenders with negative ethical motives, i.e., they suspect that the main beneficiaries of the consumption of social goods are not the claimed recipients but the enterprises and marketers, and consumers' intention to purchase social goods is therefore lowered by their ethical suspicions (Hung, 2020).

The effectiveness of information recommended by AI and humans differs significantly. Namely, consumers perceive the quality of information of AI recommendations to be higher than that of human recommendations, thus activating less persuasion knowledge in consumers. The greater the degree of reasonableness of the advertising and persuasive information obtained by a consumer is, the more positive their attitude towards the advertisement and intention to purchase the product. When the content of the message is perceived as reasonable, it triggers less consumer resistance to the persuasive message (Klingbeil et al., 2024). When consumers perceive recommendation content as valuable, they are less irritated and exhibit less avoidance (Jain et al., 2023). High-quality recommendations can streamline the information screening process and effectively help consumers make purchase decisions easily and quickly (Douglas Olsen and Pracejus, 2020). AI understands consumer preferences on the basis of consumer reviews, previous product purchases, and usage to predict new products or services that consumers are likely to enjoy (Ansari et al., 2018). Compared with human recommendations, AI recommendations optimize users' information adoption behavior, and consumers are more likely to perceive product recommendation information as useful rather than to use persuasion knowledge to resist recommendation persuasion. Empirical evidence shows that algorithmic systems are less likely to trigger persuasion knowledge in prosocial contexts (Longoni et al., 2019), particularly when their decision-making processes appear objective (Puntoni et al., 2021). Thus, the following hypothesis is proposed:

H1: Compared with human recommendations, consumers have more positive purchase intentions towards social goods when receiving AI recommendations.

3.2. The Mediating Role of Perceived Manipulative Intention

Perceived manipulative intent inferences refer to consumers' perceptions and inferences of persuasive tactics and awareness of the hidden motives employed by companies and marketers. When individuals are aware of manipulation in persuasion attempts, they infer that the source of the information is less credible and consequently react negatively (Campbell and Kirmani, 2000). If consumers perceive that a firm has strong manipulative intent, they tend to activate their persuasion knowledge and develop persuasive resistance (Zhang et al., 2018). Song et al. (2021) reported that information recipients' judgement of a recommender's manipulative intent negatively affects subsequent information adoption. In the case of online product reviews, manipulation that increases false positive reviews and hides negative reviews triggers consumer skepticism, which negatively affects purchase intention (Zhuang et al., 2018). Donation-based incentives and help-based incentives for recommendation can reduce the manipulative intent inference of the consumer, thus enhancing their purchase intention (Reimer and Benkenstein, 2018). When consumers perceive marketing persuasion as manipulative, they exhibit strong coping responses, including negative attitudes towards the brand, product, or company and negative word-of-mouth (Rahmani, 2023). Thus, this study proposes that perceived manipulative intention affects consumers' intention to purchase social goods. When consumers perceive less manipulative intent, their persuasion knowledge is less activated, so consumers are more likely to perceive the recommendation as useful information to help them in their decision making and be successfully persuaded to purchase social goods.

Drawing on the PKM's emphasis on motive attribution (Campbell and Kirmani, 2000), we posit that perceived manipulative intent serves as the key mechanism through which recommendation sources influence outcomes. This mediation pathway aligns with recent extensions of the PKM to human–AI interaction contexts (Usman et al., 2024). Previous research has suggested that people hold different beliefs about the minds of AIs and humans, i.e., that AIs do not have a mind and that humans have a mind (Garvey et al., 2023). Because AIs are nonhuman machines made by humans to serve human needs, it is difficult for consumers to infer good or selfish intentions. Because AI are often thought to be incapable of thought, emotion, and the ability to understand the meaning associated with human behavior, consumers do not typically view AIs as actors with commercially persuasive intent (Kim and Duhachek, 2020). On the other hand, consumers are more likely to infer that human experts have intentions, such as benevolent intentions to help consumers choose the most appropriate product and selfish intentions, i.e., to fulfil self-serving business goals and commercial metrics. This divergence stems from fundamental differences in mind perception: consumers ascribe mental states (e.g., intent, desire) to human recommenders but view AI as a goal-driven system lacking true intentionality (Aljarah et al., 2024). Consequently, human recommenders' commercial incentives (e.g., sales commissions) become more salient, and consumers perceive that human experts are more likely to be paid to recommend and positively evaluate products and are more inclined to view human experts' recommendations as forms of advertising (Karagür et al., 2022). In contrast, the perceived programmatic nature of AI suppresses motive inferences (Castelo et al., 2019). Thus, consumers should perceive less salience of manipulative intent in AI recommendations for social goods than in human recommendations. In summary, the recommendation method influences the level of salience of the perceived manipulative intention. Specifically, AI recommendation reduces perceived manipulative intention relative to human recommendation. Thus, the following hypothesis is proposed:

H2: Perceived manipulative intention mediates the effect of different recommendation approaches (AI vs. human) on consumers' purchase of social goods.

3.3. The Moderating Role of Goal Framing

Goal framing indicates that under loss framing, there is a greater degree of uncertainty than under gain framing (Flusberg et al., 2024). The uncertainty of loss framing is characterized by its emphasis on the loss of others' welfare caused by not purchasing social goods, which could spur the violation expectations and induce self-association and empathy for potentially adverse and negative outcomes (Kyung et al., 2024) while evoking donor empathy and reinforcing the intention to give (Majumdar and Bose, 2018). In the context of social goods purchasing, consumers' goal is to maximize assistance for those people in need (Ma et al., 2023). To overcome these uncertainties caused by loss framing, consumers seek solutions that can avoid the loss of others' welfare and risk as much as possible. To make optimal decisions, consumers are willing to exhaust all possible options and invest considerable time and energy in the decision-making process to engage in prosocial behavior (Li et al., 2019).

AI decision-making is considered to have the advantage of making optimal decisions, as AI can comprehensively collect and process multifaceted data and quickly compare and generate information schemes to maximize the common good (Puntoni et al., 2021). Consumers may perceive AI as capable of computing and identifying consumption options that optimize utilitarian outcomes (Bigman and Gray, 2018). Companies use the predictive power of AI to create hyper customized products that maximize engagement, relevance, and satisfaction (Kumar et al., 2019). Thus, when formulating recommendation information for social goods via loss framing, consumers may develop a risk-averse tendency to adopt AI recommendations, believing that AI is more capable of minimizing the loss of recipients' welfare.

Gain framing highlights the improvement in others’ benefit resulting from the purchase of social goods, which is in line with the consumer's goal of promoting the welfare of others and is more likely to activate the relevant cognitive memory of the consumer, which in turn enhances the efficiency of the consumer's cognitive processing and facilitates their quick decision-making and thus has a higher degree of approachability (Eberhardt et al., 2021). Critically, gain framing shifts consumers' cognitive focus from evaluating the recommender's intent (e.g., "Why is this source recommending this?") to pursuing the prosocial goal itself (e.g., "How can I help?"). This goal-directed processing suppresses the motivation to scrutinize differences between AI and human recommenders, as both are perceived merely as tools to achieve the salient altruistic outcome.

Furthermore, gain-framed messages align with consumers’ self-transcendent values (Abitbol and VanDyke, 2023), triggering heuristic processing where individuals prioritize message–goal congruence over analytical source evaluation (Kim, 2025). The persuasiveness of a message is enhanced when the message matches the person's goals (Lagomarsino et al., 2020). Thus, when recommendation messages for social goods are formulated via gain framing, consumers respond positively to both AI and human recommendations. Thus, the following hypotheses are proposed:

H3: Goal framing moderates the effects of different recommendation methods on consumers' intentions to purchase social goods.

H3a: When information is conveyed by loss framing, consumers are more willing to purchase AI-recommended social goods than to purchase human-recommended products.

H3b: The effects of AI and human recommendations on the intention to purchase social goods do not differ significantly when the message is conveyed via gain framing.

Loss framing emphasizes that negative consequences that may be experienced cause consumers to perceive a stronger intent to manipulate. At this point, no change in the user's actions results in a negative outcome, so change is not optional, which increases the limitations on behavioral freedom (Niesta Kayser et al., 2016). The use of controlling and assertive language in loss framing triggers strong negative emotions and fear arousal, which are perceived as more manipulative (Lee and Cameron, 2017), giving rise to greater feelings of compulsion (Xu, 2019). The use of images of sad faces and suffering in charity advertisements is believed to be a manipulative strategy because individuals perceive charities as triggering guilt by increasing psychological costs (Kang et al., 2022).

Compared with human recommendation, AI recommendation makes consumers perceive lower manipulative intent, which reduces the user's perceptions of coercion, making the user feel that he or she is not being forced to receive information. Hence, the negative impact of perceptions of coercion generated by loss framing is weakened. The reduction in the perception of compulsion moreover makes consumers feel that they have regained control of the information (Youn and Kim, 2019), which effectively reduces consumer resistance and enhances persuasion, thus making consumers more willing to choose and purchase social goods with AI recommendations.

By highlighting the improvement in the situation of others that results from the purchase of social goods, gain framing emphasizes the altruistic claims of social goods (Reinhart et al., 2007), implying that the value of public welfare product consumption benefits others. This alignment of publicly stated goals creates an effective mechanism for attributing motivations: consumers attribute recommendations to the intrinsic value of prosocial causes (e.g., helping refugees) rather than to any hidden agendas of the recommender. When information is framed to resonate with consumers' inherent prosocial motivations, it triggers positive cognitive spillover effects (Spielmann, 2021), where favorable perceptions of the information's purpose extend to the source of the recommendation, thus reducing suspicions about the recommender's manipulative intentions, whether the recommender is an AI or a human. Gain framing makes social goods more appealing to the altruistic tendencies of particular contexts or types of consumers (Ryoo et al., 2020), and consumers often have difficulty detecting the recommender's perceived manipulative intention and believe that the recommender is motivated to recommend the product out of genuine concern for social events.

H4: Goal framing and the recommendation approach interact to impact consumers' perceived manipulative intention.

H4a: AI recommendation elicits lower levels of consumer-perceived manipulative intention than does human recommendation when information is conveyed via loss framing.

H4b: There is no significant difference in the level of consumers' perceived manipulative intention induced by AI and human recommendations when information is conveyed via gain framing.

Accordingly, the research model was constructed as shown in Figure. 1 below.

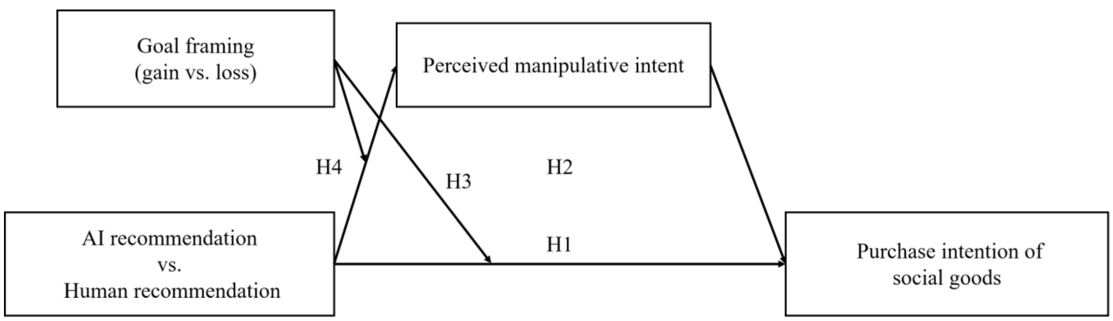

Figure 1. Theoretical Model

4. Methodology

4.1. Experiment 1

4.1.1 Sample and Data Collection

The purpose of Experiment 1 was to test the main effect of the recommendation approach (AI vs. human) on consumers' purchase intention for social goods, i.e., H1. This experiment adopted a one-way 2-level (AI recommendation vs. human recommendation) between-group experimental design. The participants were recruited through the official campus account. The selection criteria required that they have daily experience with e-commerce platforms and have not previously participated in similar experiments. We recruited a total of 164 student participants from a university in southern China, of which 4 participants failed the attention test; thus, a total of 160 pieces of valid data were obtained (54% females, Mage=21.57 years). The sample size was determined via G*Power 3.1 (Faul et al., 2009) with α=0.05, power=0.80, and a medium effect size (f=0.25), which recommended a minimum of 128 participants. Our final sample exceeded this threshold, the results are shown in table 2.

Table 2. Profile of the Participants in Experiment 1

Factor		*N* (%)
Gender	Male	73 (45.6)
	Female	87 (54.4)
Age	⩽19	24 (15.0)
	19-25	116 (72.5)
	⩾26	20 (12.5)
Monthly	Less than 2000 RMB	13 (8.1)

income	2001-5000 RMB	61 (38.1)
	5001-8000 RMB	43 (26.9)
	8000-10000 RMB	26 (16.3)
	Over 10001 RMB	17 (10.6)

4.1.2 Experimental Process

In this experiment, the bread of virtual enterprise ME Food was used as the subject of the scenario, and the theme was "Breakfast for the road angel". First, the participants were randomly assigned to two experimental groups and read different scenario materials. The participants were asked to imagine that they were in a real e-commerce shopping scenario, planning to buy bread, and had browsed information about bread on e-commerce platforms many times; then, they randomly browsed the ME company online store interface and then received the recommendation information of toast bread. Wien and Peluso (2021) was referenced to manipulate the recommendation approach. The AI recommendation group received information that "based on your preferences, the AI has given you intelligent recommendations", whereas the human recommendation group was told that "based on your preferences, human customer service has provided you with intelligent recommendations". The introduction of the public welfare product to the bread in each experimental group was the same as follows:

"ME bread, thick milk flavor, soft and tear resistant. ME toast is a public welfare product in the 'Love Breakfast Public Welfare Program' launched by ME and the Provincial Love Foundation, and ME Enterprises promise that all profits generated from the sale of bread products will be used to provide public health services to sanitation workers. All profits from the sale of bread products during the event will be used to provide sanitation workers with love breakfast".

The participants were asked to complete the questionnaire items for perception of the recommendation approach: "To what extent do you think this product recommendation information is recommended by an AI/human?" (1 = "to a very small extent", 7 = "to a great extent"). The 3-item purchase intention scale includes three items: "If you needed to, you would purchase the social goods recommended to you"; "You would be more likely to purchase the social goods recommended to you than a similar product"; and "You are highly likely to purchase a social good recommended to you if you need to purchase a similar product" (α=0.837). To control for the effects of individual experience and preferences, participants' preferences and experiences regarding social goods were used as control variables. Finally, the participants reported their demographic information.

4.1.3 Results

Manipulation check of the recommendation approach. The results of the independent samples t-test indicate that a significant difference between the two groups in terms of the perceived degree of recommendation approach: the participants in the AI recommendation group were more inclined to believe that the information was provided by AI than were the participants in the human recommendation group ($M_{\text{AI recommendation}}$ = 5.93, SD= 1.02, $M_{\text{human recommendation}}$ = 1.34, SD= 0.50, t (158) = 36.21, p < 0.001), and the participants in the human recommendation group were more inclined to believe that the information was provided by humans than were those in the AI recommendation group ($M_{\text{AI recommendation}}$ = 1.28, SD= 0.45, $M_{\text{human recommendation}}$ = 6.18, SD= 1.04, t (158) = -38.67, p < 0.001). These results suggest that the manipulation of the recommendation approach was successful, the results are shown in table 3.

Table 3. Descriptive Statistics of the Experimental Group for the Key Variables in Experiment 1

Variable	Group	M	SD
Purchase intention of social goods	Human	3.83	1.18
	AI	5.52	1.56
Social goods participation experience	Human	4.57	1.45
	AI	4.72	1.54
Bread product preferences	Human	4.90	1.60
	AI	4.75	2.08

Main effects analysis. The ANCOVA results (see table 4) indicate that, after controlling for participants' social goods participation experience and bread product preferences, the main effect of the recommendation method on the purchase intention of social products is significant ($F(1,156)$= 59.26, p<0.001, η^2=0.28). Specifically, the AI recommendation group's willingness to purchase social products (M=5.52, SD=1.56) is significantly higher than that of the human recommendation group (M =3.83, SD=1.18), thus supporting Hypothesis H1.

Table 4. ANCOVA Results of the Impact of Recommendation Methods on the Purchase Intention of Social Products in Experiment 1

Model/predictor	Sum of square	df	Mean square	F	P value	(Partial)η²
Corrected model	120.669	3	40.223	21.352	< 0.001***	0.291
Error	293.88	156	1.884			
Total	3908.333	160				
Covariates						
Social goods participation experience	2.936	1	2.936	1.559	0.214	0.010
Bread product preferences	0.576	1	0.576	0.306	0.581	0.002
Main effect						
Recommendation approach	111.627	1	111.627	59.255	< 0.001***	0.275

Note: Dependent variable = Purchase intention of social products, $R^2 = 0.291$, adjusted $R^2 = 0.277$. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Control variable analysis. For the participants' social goods participation experience, the results of the independent samples t-test indicate no significant difference between the AI and human recommendation groups ($M_{\text{AI recommendation}}$ =4.72, SD= 1.54, $M_{\text{human recommendation}}$ =4.57, SD= 1.45, t (158) = 0.62, p =0.54); there was also no significant difference between the AI and human recommendation groups in terms of bread product preferences ($M_{\text{AI recommendation}}$ =4.75, SD= 2.08, $M_{\text{human recommendation}}$ =4.90, SD= 1.60, t (158) = -0.51, p =0.61).

The results of Experiment 1 support Hypothesis H1; that is, compared with human recommendation, AI recommendation can significantly increase consumers' intention to purchase social goods. Notably, in the next experiment, the mediating effect of perceived manipulative intention was tested to determine whether it was supported.

4.2. Experiment 2

4.2.1 Sample and Data Collection

The purpose of Experiment 2 was twofold: to reverify the effect of the recommendation approach (AI vs. human) on consumers' intention to purchase social goods and to test whether the perceived manipulative intention mediated the main effect in Experiment 1. In this experiment, a one-way 2-level (recommendation approach: AI vs. human recommendation) between-group experimental design was adopted. A total of 108 participants were recruited from the Credamo platform (a Chinese internet data survey company). To maintain the quality of the data, the participants were required to fulfil the following criteria: (1) no prior participation in AI-related experiments, (2) active milk consumption (>2 times/week), and (3) IP address uniqueness verification. Additionally, we discarded the data of participants who did not pass the attention screening; as a result, 100 valid data points were obtained (51% females, Mage = 29.82 years). The sample size was ascertained using G*Power 3.1 (Faul et al., 2009) with α=0.05, power=0.80, and a medium effect size (f=0.35), suggesting that a minimum of 98 participants should be included. In our study, the final sample size surpassed this threshold (see table 5).

Table 5. Profile of the Participants in Experiment 2

Factor		*N* (%)
Gender	Male	49 (49)
	Female	51 (51)
Age	≤25	11 (11)
	26-32	66 (66)
	≥33	23 (23)
Education	High school or less	3 (3)
	College/university	69 (69)
	Graduate school	28 (28)
Monthly income	Less than 2000 RMB	4 (4)
	2001-5000 RMB	37 (37)
	5001-8000 RMB	39 (39)
	8000-10000 RMB	20 (20)
	Over 10001 RMB	10 (10)

4.2.2 Experimental Procedure

In this study, the milk of the virtual dairy K enterprise was used as the scenario, and the theme of the social marketing activity was "Plant Better, Make the Desert Better". The choice of scenario was based the three considerations, First, many daily use scenarios exist, and they are useful, universal and affordable to avoid experimental errors caused by the specificity of the experimental products. Second, the constructed social goods must have a high degree of fit with social marketing activities (Myers and Kwon, 2013), which can help the experimental participants understand the experimentally set scenario quickly. Third, the experimental participants' possible preference for real brands should be eliminated.

The participants were randomly divided into two groups. First, the participants were asked to read a passage of experimental material, and they were asked to imagine that they were very concerned about the ecological environment of the desert region and had browsed charitable and social marketing activities related to desert ecological protection many times. This procedure was used to exclude the interference of consumers' original attitudes towards the charity project in the experimental results. The participants were told that they had recently planned to buy milk and had searched for information about milk on e-commerce platforms several times. At this time, they randomly browsed the homepage of the online store of enterprise K and received the recommendation information of "Desert + Organic" milk. The AI recommendation group shows that "based on your preferences, the AI has given you intelligent recommendations", whereas the human recommendation group was told that "based on your preferences, customer service has provided you with intelligent recommendations". The public welfare product milk product was described as follows:

*"Desert + Organic Milk, high calcium and high protein, healthy and nutritious good milk. Desert + Organic milk is a public welfare product in the greening public welfare project initiated by K Enterprises in conjunction with the American Greening Foundation. For every set of this product purchased by consumers, the enterprise promises to donate 1 dollar to the Sahara regional government and use it for environmental improvement in desert area*s".

To ensure that the participants read and understood the experimental material carefully, all the subjects were required to pass an attention test question related to social goods. Then, they were asked to complete the manipulation items for the perception of the recommendation: "To what extent do you think that this product recommendation is an AI/human recommendation" (1 = to a very small extent, 7 = to a very large extent). The subjects reported their perceived manipulative intention and intention to purchase milk. The perceived manipulative intention scale was developed on the basis of Edwards et al. (2002) and consists of the following three items: "I think the recommendation is trying to influence my purchasing decision, which disgusts me"; "I think the recommendation is trying to persuade me to achieve its own marketing objectives rather than to help me make an optimal decision, which bores me"; and "I think the recommendation is trying to manipulate my purchasing behavior, which is unacceptable to me" (1=strongly disagree, 5=strongly agree, α=0.920). The measures of purchase intention were the same as those in Experiment 1. Finally, the participants were asked to report their experience with social goods participation, milk product preferences, and demographic information.

4.2.3 Data Analysis

Manipulation check of the recommendation approach. The results (table 6) of the independent samples t test indicate a significant difference between the two recommendation approaches. The participants in the AI recommendation group were more inclined to believe that the information was provided by AI than were the participants in the human recommendation group ($M_{\text{AI recommendation}}$ = 6.26, SD= 0.85, $M_{\text{human recommendation}}$ = 1.22, SD= 0.42, t (98) = 37.52, p < 0.001), and the participants in the human recommendation group were more inclined to believe that the information was provided by humans than were those in the AI recommendation group ($M_{\text{AI recommendation}}$ = 1.26, SD= 0.44, $M_{\text{human recommendation}}$ = 5.84, SD= 1.33, t (98) = -23.10, p < 0.001). These findings suggest that the manipulation of the recommendation approach was successful. The test results of the control variables revealed no significant difference between the two groups in terms of participation in social goods and milk product preferences.

Table 6. Descriptive Statistics of the Experimental Group for the Key Variables in Experiment 2

Variable	Group	M	SD
Purchase intention of social products	Human	3.77	1.16
	AI	6.23	0.93
Social goods participation experience	Human	5.14	1.52
	AI	5.27	1.72
Bread product preferences	Human	5.12	1.85
	AI	5.02	2.15

Reliability test. The Cronbach's alpha coefficient of the perceived manipulative intention scale is 0.920 and that of the social goods purchase intentions scale is 0.943, both of which are greater than 0.8, indicating that the scales have a relatively good level of reliability.

Main effects test. The ANCOVA indicates that, after controlling for participants' social goods participation experience and bread product preferences, the main effect of the recommendation method on the purchase intention of social products is significant ($F(1,96)= 135.45$, $p<0.001$, $\eta^2= 0.59$). Specifically, the AI recommendation group's willingness to purchase social products ($M=6.23$, $SD=0.93$) is significantly higher than that of the human recommendation group ($M =3.77$, $SD=1.16$), thus supporting Hypothesis H1 (see figure 2 and table 7).

Table 7: ANCOVA Results of the Impact of Recommendation Methods on the Purchase Intentions of Social Products in Experiment 2

Model/predictor	Sum of square	df	Mean square	F	P value	(Partial)η²
Corrected model	154.328	3	51.443	46.501	< 0.001***	0.592
Error	106.202	96	1.106			
Total	2760.230	100				
Covariates						
Social goods participation experience	0.026	1	0.026	0.024	0.878	0.000
Bread product preferences	1.318	1	1.318	1.192	0.278	0.012
Main effect						
Recommendation approach	149.839	1	149.839	135.445	< 0.001***	0.585

Note: Dependent variable = Purchase intention of social products, $R^2 = 0.592$, adjusted $R^2 = 0.580$. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

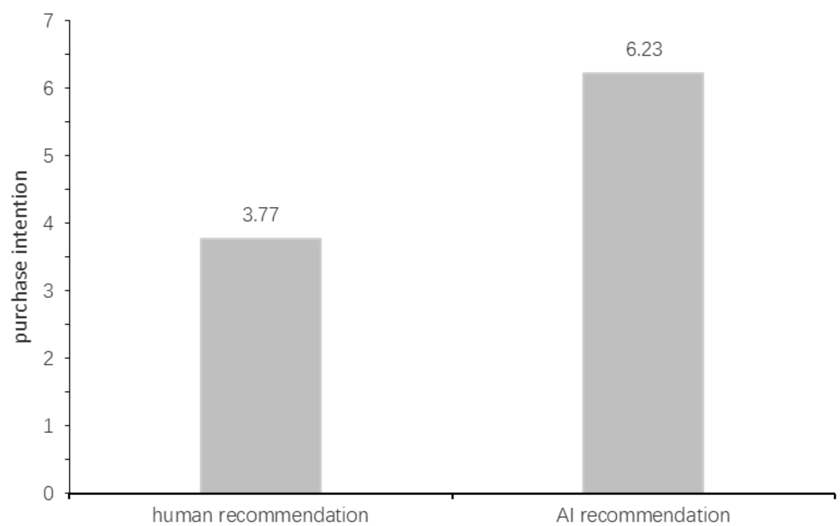

Figure 2. Effect of the Recommendation Approach on Consumers' Intention to Purchase Social Goods

Mediating effect test. SPSS PROCESS Model 4, combined with the bootstrap method, was used to test the results (see Figure 3), which revealed that the mediating effect of perceived manipulative intention in the recommendation approach on consumers' intention to purchase social goods was significant (nondirected path effect = 0.16, SE = 0.217, 95% CI:[1.211,2.079], not including 0). Thus, H2 was validated.

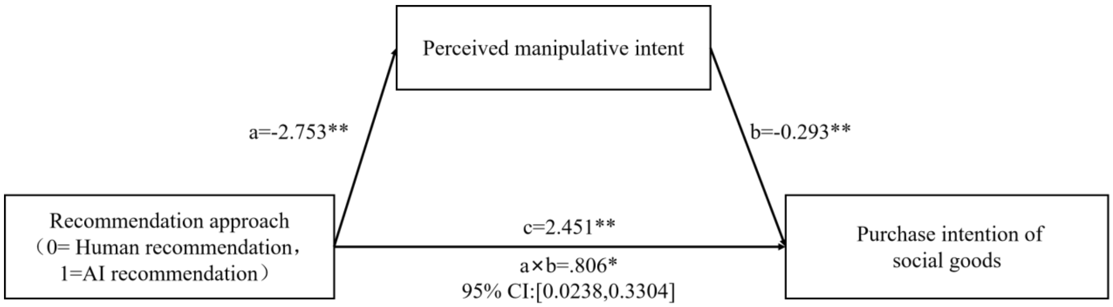

Figure 3. Mediating Effect of Perceived Manipulative Intention in Experiment 2

Control variable analysis. For the participants' social goods participation experience, the results of the independent samples t test indicate that no significant difference between the AI and human recommendation groups ($M_{\text{AI recommendation}}$ = 5.27, SD= 1.72, $M_{\text{human recommendation}}$ = 5.14, SD = 1.52, t (98) = 0.39, p =0.70) as well as between the AI and human recommendation groups in terms of bread product preferences ($M_{\text{AI recommendation}}$ = 5.02, SD = 2.15, $M_{\text{human recommendation}}$ = 5.12, SD = 1.85, t (98) = -0.25, p = 0.80).

The results of Experiment 2 once again verify the advantage of AI recommendation over human recommendation in enhancing consumers' intention to purchase social goods. Experiment 2 also examined the mediating role of perceived manipulative intention. The results showed that perceived manipulative intention played a significant mediating role between the recommendation approach and consumers' intention to purchase social goods. This finding confirms H2 and further reveals the internal mechanism by which the recommendation approach affects consumer behavior. These results not only reinforce the findings of Experiment 1 but also further demonstrate the advantages of AI recommendation and its effectiveness in reducing perceived manipulative intention across different products and contexts.

4.3. Experiment 3

4.3.1 Sample and Data Collection

The purpose of Experiment 3 was to test whether goal framing (gain framing vs. loss framing) moderates the effect of the recommendation approach (AI vs. human recommendation) on consumers' intention to purchase social goods via the perceived mediating effect of perceived manipulative intention. For this experiment, a two-factor between-group experimental design of 2 (recommendation approach: AI vs. human recommendation) × 2 (goal framing: gain vs. loss framing) was adopted, and a total of 150 subjects were recruited via the Credamo platform. To maintain the quality of the data, participants were required to fulfil the following criteria: (1) no prior participation in AI-related experiments, (2) recent purchase of wearable devices (>1 purchase in the past 6 months), and (3) IP address was verified as unique. Finally, 145 participants were included in the data analysis, 5 of whom initially failed the attention test and then passed the attention test (53% females, and Mage = 26.30 years). The sample size was ascertained using G*Power 3.1 (Faul et al., 2009) with α=0.05, power=0.95, and a medium effect size (f=0.25), which suggested that a minimum of 132 participants be included. In our study, the final sample size surpassed this threshold (see table 8).

Table 8. Profile of the Participants in Experiment 3

Factor		*N* (%)
Gender	Male	68 (47)
	Female	77 (53)
Age	≤18	11 (7.59)
	19-25	81 (55.86)
	26-32	40 (27.59)
	≥33	13 (8.96)
Education	High school or less	6 (4.14)
	College/university	120 (87.76)
	Graduate school	19 (13.10)
Monthly income	Less than 2000 RMB	17 (11.72)
	2001-5000 RMB	25 (17.24)
	5001-8000 RMB	34 (23.45)

	8000-10000 RMB	44 (30.34)
	Over 10001 RMB	25 (17.24)

4.3.2 Experimental procedure

This experiment constructs the virtual brand Depp's sports bracelet as a public welfare product, where the village children's sports public welfare program is the social marketing program. The participants were informed that Depp will donate a portion of the profits from the sales of the bracelet to support the village children's sports social marketing program.

The participants were randomly assigned to one of four experimental groups and were first asked to read a passage of experimental material. The participants were asked to imagine that they were very concerned about improving rural children's physical education. Recently, the purchase of sports bracelets was linked to this initiative and are commonly used to search for and browse related product information. One day by chance, they visit the homepage of the Depp flagship store; at this time, the sports bracelet recommendation message pops up on the homepage, and the subjects randomly read information concerning the social goods as recommended by the AI or a human.

The recommendation approach items follow the method in Experiment 1. The manipulation of goal framing was based on the manipulation methods of Ku et al. (2018). The gain framing was expressed as follows: "Depp will donate a portion of its profits to support the sports charity program for rural children. With your help, rural children will have professional and safe sports fields, and their bodies will be able to achieve healthy growth and development". The loss framing was presented as follows: "Depp will donate a portion of its profits to support the rural children's sports charity program. Without your help, rural children will not have professional and safe playing fields, and their bodies will not be able to achieve healthy growth and development".

The participants were asked to report their intention to purchase the Depo sport bracelet (1 = "very reluctant", 7 = "very willing") and to answer an attention test question ("Who are the beneficiaries of the social goods?"). The manipulation verification item for the perception of the recommendation approach was then measured with the same scale as that used in Experiment 1. The manipulation verification item for measurement goal framing, "Which information do I think the recommendation emphasizes?" (1 = harms of not purchasing this product, 7 = benefits of purchasing this product), was measured. The subjects then reported their maximizing mindset (1="strongly disagree", 7="strongly agree"), which consisted of the following five items: "I do not like to settle for 'good enough'", "I never settle for second best; no matter what I do, I expect the highest of myself", "I am a maximizer and I will wait for the best option, no matter how long it takes", "I never settle for less", and "I always try to choose the best for whatever I need". These item were drawn from the scale used by Dalal et al. (2015). Finally, participants' experiences of social goods engagement and opinions on the exercise bracelet, as well as demographic information, were measured via the scale used in Experiment 1.

4.3.3 Data Analysis

Manipulation effect check. Using the degree of recommendation approach perception as the dependent variable, an independent samples t test was conducted on the AI vs. human recommendation groups. The subjects in the AI recommendation group perceived the approach to be driven by AI more strongly ($M_{\text{AI recommendation}}$ = 3.14, SD = 1.87 vs. $M_{\text{human recommendation}}$ = 5.96, SD = .97, t (143)= -11.46, p < 0.001); the participants in the human recommendation group perceived the recommendation approach to be human more strongly ($M_{\text{AI recommendation}}$ = 2.55, SD = 1.47 vs. $M_{\text{human recommendation}}$ = 5.25, SD = 1.84, t(143) = 9.77, p = .039). Thus, the manipulation of the recommendation approach in this experiment was successful. An independent samples t test was conducted using the perception of goal framing as the dependent variable. The perceived benefits of purchasing the product were significantly greater in the gain framing group than in the loss framing group ($M_{\text{gain framing}}$ =6.23, SD=0.79 vs. $M_{\text{loss framing}}$ =2.99, SD=2.00, t(143)=12.97, p<.001). This finding indicates that the manipulation of goal framing was successful (see table 9).

Table 9. Descriptive Statistics of the Experimental Group on the Key Variables in Experiment 3

Variable	Group	M	SD
Purchase intention of social products	Human-gain	5.39	1.04
	Human-loss	4.39	1.40
	AI-gain	5.60	0.92
	AI-loss	5.51	1.19
Social goods participation experience	Human-gain	5.30	0.75
	Human-loss	5.31	1.20
	AI-gain	5.42	1.01
	AI-loss	5.65	0.85

Social goods preference	Human-gain	5.53	0.94
	Human-loss	5.29	1.20
	AI-gain	5.63	0.63
	AI-loss	5.47	0.91

Reliability tests. The Cronbach's alpha coefficient of the perceived manipulative intention scale is 0.866, that of the social goods purchase intention scale is 0.896, and that of the maximization mindset scale is 0.920, indicating that the scales have relatively good reliability.

Main effects test. The ANCOVA indicates that, after controlling for participants' social goods participation experience and bread product preferences, the main effect of the recommendation method on the purchase intention of social products is significant ($F(1,139)=9.74$, $p<0.01$, $\eta^2=0.07$), thus supporting Hypothesis H1. The main effect of goal framing on the purchase intention of social products is significant ($F(1,139)= 9.81$, $p=<0.01$, $\eta^2= 0.07$). Moreover, the interaction effect between the recommendation method and goal framing is significant ($F(1,139)=5.48$, $p<0.05$, $\eta^2=0.04$), indicating that goal framing moderates the impact of the recommendation method on purchase intention (see table 9).

Table 10. ANCOVA Results of the Impact of Recommendation Methods on the Purchase Intentions of Social Products in Experiment 3

Model/predictor	Sum of square	df	Mean square	F	P-value	(Partial)η²
Corrected model	66.965	5	13.393	12.284	< 0.001***	0.306
Error	151.551	139	1.090			
Total	4188.000	145				
Covariates						
Social goods participation experience	15.855	1	15.855	14.542	< 0.001***	0.095
Social goods preference	3.837	1	3.837	3.520	0.063	0.025
Main effect						
Recommendation approach	10.616	1	10.616	9.736	0.002**	0.065
Goal framing	10.694	1	10.694	9.809	0.002**	0.066
Interaction effects						
Recommendation approach × Goal framing	5.976	1	5.976	5.481	0.021*	0.038

Note: Dependent variable = Purchase intention of social products, $R^2 = 0.405$, adjusted $R^2 = 0.326$. * $p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Mediation effect test. The results revealed that the participants in the AI recommendation group had significantly lower perceived manipulative intentions than did those in the human recommendation group ($M_{\text{AI recommendation}} = 2.38$, $SD = .86$ vs. $M_{\text{human recommendation}} = 2.77$, $SD = 1.06$, $F(1, 143) = 6.32$, $t = 2.42$, $p = 0.013$). By using the bootstrapping method (Process Model 4, bootstrap 5000; Hayes, 2017), a mediation effect test was conducted with perceived manipulative intention as the dependent variable, the recommendation method as the independent variable (0 = human recommendation, 1 = AI recommendation), and perceived manipulative intention as the mediating variable. The results showed that the mediating effect of perceived manipulative intention was significant (nondirected path effect = 0.16, SE = 0.15, 95% CI: [0.0238, 0.3304]). The results therefore support H2.

Alternative explanation analysis. A maximizing mindset is defined by two characteristics: a goal to choose the best and a tendency to thoroughly compare alternatives (Xia and Bechwati, 2021). Prior studies indicate that individuals with a maximizing mindset exhibit heightened sensitivity to persuasive attempts because of their tendency to exhaustively evaluate options and avoid suboptimal choices (Mao, 2016; Nardini and Sela, 2019). This characteristic makes them more likely to perceive external recommendations (whether AI or human) as manipulative, thereby reducing their purchase intention. Specifically, in the context of social goods recommendations, maximizers may scrutinize the altruistic claims of the recommendation source, suspecting hidden profit motives. Furthermore, the maximization mindset has been proven to influence the inclination to use AI financial advisors in personal financial decision-making through the perception of enhanced algorithmic effectiveness and reduced algorithmic aversion (Silber et al., 2025). This research considered maximizing mindfulness as a possible alternative explanation between the recommendation approach (AI vs. human recommendation) and consumers' intention to purchase public welfare products. Our data revealed no significant difference between the two groups of participants in terms of maximizing mindfulness ($M_{\text{AI recommendation}}$ = 4.95, SD = 1.21 vs. $M_{\text{human recommendation}}$ = 4.63, SD = 1.29, F(1, 143) =0.104, t = -1.54, p = 0.748). Maximizing mindfulness alone was put into PROCESS as a mediator variable and failed to have a mediating effect (nondirected path effect =0.021, SE = 0.03, 95% CI: [-0.0698, 0.0741]). The main effect of recommendation style still held when maximizing mindfulness was used as a covariate (F(1, 143) = 10.78, p = 0.001, η^2_p = .071), the results are shown in figure 4.

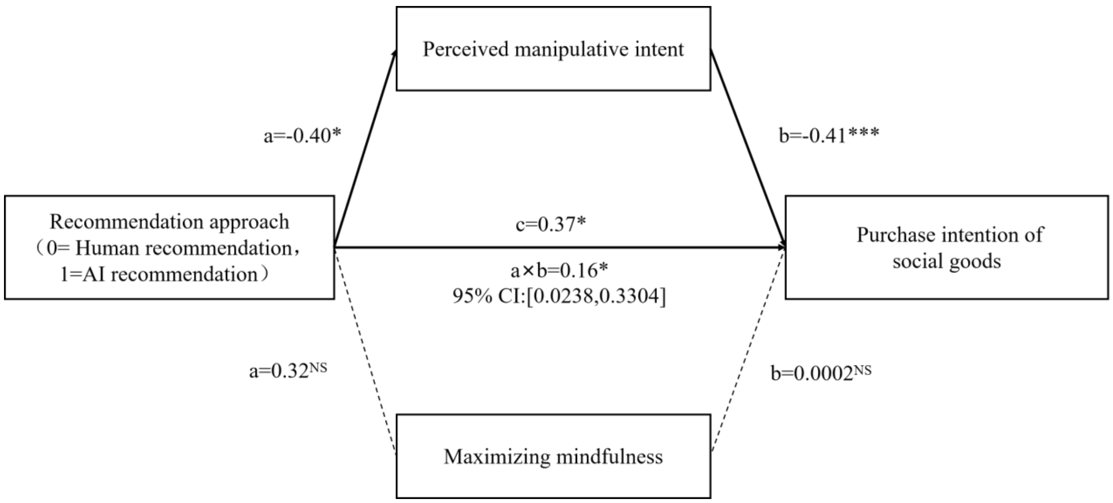

Figure 4. Mediating Effect of Perceived Manipulative Intention in Experiment 3

Moderation effect test. Using 2 (recommendation approach: AI vs. human) × 2 (goal framing: gain framing vs. loss framing) two-factor analysis of variance (ANOVA), the results revealed main effects for both recommendation approaches (F(1, 143)=12.14, p=0. 001) and indicated that goal framing is significantly supported (F(1, 143) = 8.13, p = 0.005). Moreover, the interaction effect of the recommendation approach and goal framing is also significant (F(1, 141) = 5.73, p = 0.018). Thus, H3 was validated.

The simple effects analysis (figure 5) indicated that consumers had greater intentions to purchase AI recommendation social goods than under human recommendation when information was conveyed via loss framing ($M_{\text{AI recommendation}}$ =5.51, SD=0.19 vs. $M_{\text{human recommendation}}$ =4.39, SD=0.19, F(1, 141)=16.93, p<0.001, η2p=0.107, 95% CI: [0. 581,1.656]). However, there was no significant difference between the effects of AI and human recommendations on the intention to purchase social goods when the message was conveyed using gain framing ($M_{\text{AI recommendation}}$ =5.60, SD=0.19 vs. $M_{\text{human recommendation}}$ =5.39, SD=0.19, F(1, 141)=0.607, p=0.437). Thus, H3a and H3b were both validated.

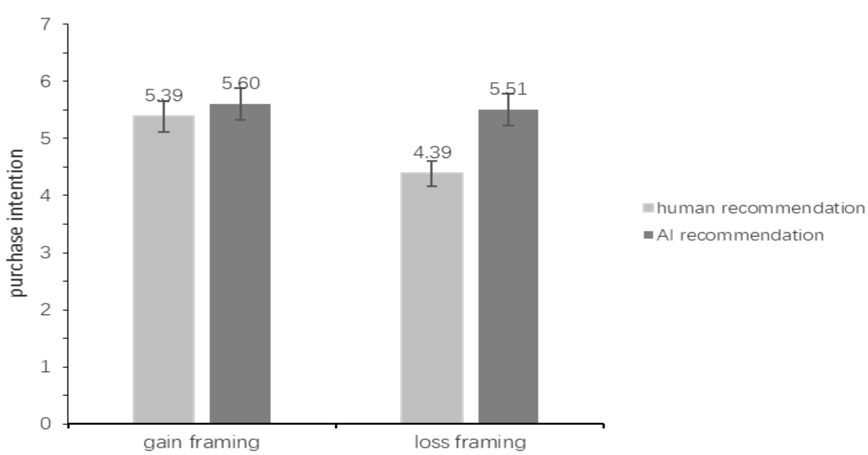

Figure 5. Moderation Effect of Goal Framing on the Effect of the Recommendation Approach on Consumers' Intention to Purchase Social Goods

Moderated mediation effect test. A moderated mediated effects analysis was conducted using PRCOCESS (Model 8, 5,000 bootstraps; Hayes, 2017) with sports bracelet purchase intention as the dependent variable, the recommendation approach as the independent variable, goal framing as the moderator variable, and perceived manipulative intention as the mediator variable. The results show that perceived manipulative intention mediated the effect of the interaction term of recommendation style and goal framing on the purchase intention for sports bracelets (nondirected path effect = 0.2752, SE = 0.13, 95% CI: [0.0444, 0.5580]). Specifically, when the information was presented in a loss framing, the mediating effect of perceived manipulative intention was significant, with a confidence interval that did not include 0 (95% CI: [0.1022, 0.4917]) and an effect size of 0.2833. When the information was presented in gain framing, the mediating effect of perceived manipulative intention was not significant, with a confidence interval that included 0 (95% CI: [-0.1630, 0.1749]). The results support H4, H4a, and H4b.

Control variable analysis. The results of ANCOVA indicate that participants' social goods participation experience has a significant effect on the purchase intention of social products ($F(1,139)= 14.54$, $p=<0.001$, $\eta^2= 0.10$), while the effect of product preference is not significant ($F(1,139)= 3.52$, $p=<0.063$, $\eta^2= 0.03$). After controlling for the above variables, the main effect of the recommendation approach on the purchase intention of social goods remained significant ($p=0.002<0.01$).

The results of Experiment 3 not only verified the findings of the previous two experiments but also further confirmed the moderating role of goal framing (gain vs. loss) between recommendation approaches and consumers' purchase intentions. The results show that AI recommendations are associated with lower perceived manipulative intention in loss framing, whereas there is no significant difference between the two recommendation approaches in terms of perceived manipulative intention in gain framing. This finding supports H3 and H4.

5. Discussion

Social marketing has received widespread attention because of its positive impact on facilitating a win–win situation for enterprises, society, the government and consumers (Bai and Yan, 2020). Additionally, the rise of social goods relying on e-commerce platforms has led to the use of artificial intelligence tools to achieve better marketing performance (Arango et al., 2023). In the context of AI marketing, the way in which enterprises recommend social goods to consumers and increase their purchase intentions still constitutes an important direction for future research and practice in the field of marketing (Cheng et al., 2023; Luan and Phan, 2024). This paper takes the purchase of social goods on e-commerce platforms as the background and the PKM and goal framing theory as the theoretical basis and compares the effect of AI recommendation with that of human recommendation. More specifically, it examines the effect of perceived manipulative intention on the relationship between the recommendation approach (AI vs. human) and consumers' purchase intentions and explores the boundary mechanism of goal framing. By conducting three experiments, the following conclusions are drawn.

First, recommendation approaches (AI vs. human) have significant effects on consumers' purchase intentions for social goods. AI recommendation has the characteristics of more comprehensive rationality and fast response, whereas human recommendation has the characteristics of high levels of emotional experience and interpretability. On the basis of individuals' social signaling motivation theory, combined with the characteristics of social goods, individuals want to maintain pure altruism, i.e., driven by personal signaling motivation, when purchasing social goods. AI recommendations that are considered mindless are better, whereas human recommendations with emotions and thoughts are worse. This difference suggests that AI recommendations can more effectively match consumer preferences and needs, which makes it easier for consumers to develop a sense of trust (Yang and Wibowo, 2022) and identification when confronted with recommended information, reduces the activation level of persuasion knowledge, and thus enhances consumers' purchase intentions. This finding is consistent with those of previous studies, such as that of (Wien and Peluso, 2021), who noted that AI recommendations enable personalized content to be pushed through big data analysis, which increases consumers' purchase intentions.

Second, perceived manipulative intention mediates the relationship between the recommendation approach and consumers' purchase intentions for social goods. The recommendation approach (AI vs. human) has a significant effect on perceived manipulative intention, which is evident in the fact that an AI recommendation that relies on no mental ability has a relative advantage in reducing perceived manipulative intention, whereas a human recommendation with mental ability has greater perceived manipulative intention. The results reveal that different recommendation approaches (AI vs. human) affect consumers' intentions to adopt information through perceived manipulative intention, which in turn affects the effectiveness of social goods.

Third, message goal framing plays a moderating role in the relationship between recommendation styles and the intention to purchase social goods. Under different goal frames, the same recommendation approach may produce different recommendation effects, i.e., change an individual's level of adoption of the recommended approach. When the presentation of information is aligned with a person's cognitive needs, it improves an individual's acceptance of the information. Specifically, the application of loss framing makes consumers more concerned about avoiding losses. In this case, the AI recommendation, owing to its high logic and objectivity, can determine the solution that optimizes the outcome and minimizes the loss, which is highly compatible with consumers' focus and thus enhances their purchase intention. In contrast, in gain framing, consumers are concerned with the benefits gained, so there is little difference in the perceived manipulative intention between the two recommendation approaches. These results not only expand the scope of research on the relationship between recommendation methods and perceived manipulative intention but also provide empirical evidence for enterprises' recommendation strategy choices in different contexts.

5.1. Theoretical Contributions

First, this paper introduces AI recommendations into the field of social goods marketing, which enriches the theoretical evidence of use AI as tools in the field of social marketing. Previous studies have focused mostly on two recommendation approaches (AI vs. human) in terms of their truthfulness and interpretability (Jago, 2019), their comparison in terms of realism, interpretability (Jago, 2019) and other characteristics (Chang and Park, 2024) and the influence and mechanism of individual consumer behavior. Situational factors have focused on the subjectivity and objectivity of the task (Castelo et al., 2019) in the medical field (Longoni et al., 2019) and the favorable or unfavorable outcomes of the decision (LaMothe and Bobek, 2020). Only a few studies have explored the impact on social marketing, and there is debate about whether AI technology can inspire a sense of morality in consumers (LaMothe and Bobek, 2020; Zhou et al., 2022). This study reveals the unique advantages of AI in promoting social goods marketing by introducing the influence mechanism of AI recommendation into the field of social goods. This research not only fills the research gap in the application of AI technology to social marketing scenarios (Mao et al., 2020) but also expands the value scope of AI recommendation systems—shifting from pure commercial profit-driven objectives to the dual empowerment of social and commercial values.

Second, this research expands the application scenarios of PKM model by linking the PKM with the persuasion approach of AI recommendations. Previous studies employing the PKM have shown that combining the PKM with attitude formation theory delineates the pros and cons of persuasion knowledge for consumers' assessment of location-based advertising, which in turn affects consumers' attitudes, personal information disclosure, and acceptance (Li et al., 2023). Prior PKM studies have focused primarily on interactions between human persuaders (e.g., salespeople, advertising endorsers) and consumers (Eisend and Tarrahi, 2022), emphasizing consumers’ perceptions of and strategies to cope with persuasive human intentions. This study innovatively incorporates AI recommendations into the PKM analytical framework and finds that consumers’ perceived manipulative intention towards AI recommendations is significantly lower than that towards human recommendations and that this difference moreover affects purchase intentions through a mediating effect. AI’s no personalized characteristics may reduce consumers’ defensive mindsets, making them more receptive to recommended information (Xie et al., 2022).

Third, this research brings PKM model and goal framing theory together by validated the mediating role of perceived manipulative intention and moderating role of goal framing in the context of AI marketing. Previous studies have address PKM model and goal framing theory separately, and relatively few studies have examined their role in situations of social goods marketing campaigns (Spence and Pidgeon, 2010). For instance, most current research on perceived manipulative intention has been conducted in the marketing domain and explores how to reduce perceived manipulative intention through AI and procedural optimization. In this paper, we creatively combine the PKM with goal framing and finds that the use of gain (vs. loss) framing can change the impact of the recommendation approach (AI vs. human) on the effectiveness of the purchase of social goods. This study explores the goal framing effect in the context of social marketing by using AI recommendations, which marks a useful expansion and innovation of theoretical application scenarios. By integrating goal framing theory into the effectiveness evaluation system of recommendation technology, this study reveals the interaction mechanism between information presentation styles and the characteristics of recommendation agents. Unlike previous research that focused solely on attributes such as recommendation source credibility and expertise (Wang et al., 2020; Kim et al., 2021), this study further demonstrates that recommendation effectiveness does not merely depend on "who is recommending"; rather, it is more significantly influenced by "how to recommend" (i.e., framing strategies).

5.2. Management Insights

First, the advantage of AI in social goods marketing provides actionable guidelines for e-commerce platform use AI technology to address social goods issues. Social goods often face promotion challenges due to their weak commercial attributes (Schamp et al., 2019) and high user cognitive costs (Hermann, 2022). However, the efficient reach of AI recommendations can overcome these limitations. Enterprises should fully utilize the efficiency and precision of AI recommendations to provide personalized recommendation services through in-depth analysis of consumer needs. For example, an e-commerce platform focusing on environmental protection products can recommend social goods with environmental attributes, such as biodegradable water cups or recycled paper notebooks, on the basis of consumers' purchase and browsing history. For example, by using AI to identify users who frequently participate in environmental protection topics, sustainable consumer goods with traceable carbon footprints can be recommended in a targeted manner, thereby strengthening the perception of consumption as a contribution. This type of recommendation approach not only increases consumers' interest in products but also saves them time and helps them make quick purchasing decisions, thus enhancing the promotion of social goods.

Second, firms should reduce perceived manipulative intention during the persuasion process of consusmers' social goods purchase. This paper verifies that under the mediating effect of perceived manipulative intention, different recommendation approaches have an impact on consumers' purchase intentions for social goods. When recommending products or services to consumers, enterprises should focus on reducing the perceived manipulative intention. Transparency of the recommendation logic should be achieved by disclosing the basis of AI recommendations to users, such as historical behaviors, social attributes, and preferences of similar users, to avoid suspicion caused by black-box operations (Jago, 2019). For example, when recommending donation programs, commonwealth organizations can use AI recommendations to match donors' areas of interest, such as education, health or environmental protection, rather than relying solely on human recommendations. This approach can lead donors to perceive the neutrality and objectivity of the recommendation, thus increasing trust and acceptance. In addition, enterprises can shape AI recommendations as information assistants rather than as marketing entities. They can thus weaken the commercial orientation through interactive language and highlight the instrumental value of AI in helping users make efficient decisions in the era of information overload. For example, when promoting social goods, they can use a more transparent and truthful recommendation approach to avoid giving consumers the impression of overselling.

Third, enterprises should choose the appropriate information frame according to different recommendation approaches (AI vs. human). For example, when AI recommendation is used, loss framing may be more appropriate. By emphasizing the potential losses that may be incurred if a product is not purchased, this framing amplifies the users' perception of potential losses, which stimulates their purchasing behavior. In the case of human recommendation, gain framing may be more effective. This framing emphasizes the direct benefits from purchasing the product, highlights the specific benefits and values of taking action, and strengthens the users' initiative to make a purchase. This targeting strategy helps increase the persuasiveness of the recommended information and consumers' purchase intentions. For example, a public interest crowdfunding platform may use loss framing, such as "Help save endangered species from extinction", when using AI to recommend projects, and gain framing, such as "Join us in guarding endangered species", when providing human recommendations. This differential framework strategy, which is based on the recommendation subject, can maximize the rational persuasion advantage of AI, effectively enhance the persuasiveness and influence of the suggestions, and thereby achieve precise improvement in the marketing effect of social goods.

5.3. Limitations and Future Research Directions

First, although the internal validity of the laboratory experiment was high, only the food type of social goods was selected as the stimulus and lacked external validity. Future studies could enhance the external validity of the experiment through field experiments and broaden the selection of social goods to other types of products to improve the applicability of the findings. For example, Lv and Huang (2024) explored the application of personalized recommendations to charity advertisements and reported that, owing to a decrease in perceived autonomy, they would lead to a lower intention to donate.

Second, consumers' purchase intentions for social goods may be affected by other factors in addition to the recommendation method, such as the individual's degree of involvement, the type of regulatory focus, income, values, etc., and these have yet to be measured. Future research can further consider the impacts of the degree of anthropomorphizing, information orientation, and degree of involvement in AI recommendation contexts.

6. Conclusion

This study bridges critical gaps in understanding how AI versus human recommendations influence social goods purchases. By integrating the PKM with goal framing theory, we demonstrate that AI recommendations enhance purchase intentions by reducing perceived manipulative intent—particularly under loss-framed messages where algorithmic objectivity aligns with consumers' loss-aversion motivations. These findings advance prosocial marketing literature in three ways: (1) revealing AI's unique advantage in ethical consumption contexts, (2) establishing perceived manipulative intent as a key mediator in human-AI persuasion, and (3) identifying goal framing as a boundary condition for recommendation effectiveness. For practitioners, our results provide actionable guidelines for deploying AI recommenders in social marketing campaigns.

Acknowledgment

The authors would like to express their sincere gratitude to the editors and reviewers for their thoughtful feedback and guidance throughout the review process. This study was funded by the National Social Science Fund of China (No. 22AGL016).

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