The Impact of Humans vs. AI Recommendation on Consumer Reactions to Products Exposure

Electronic Commerce Research
https://doi.org/10.1007/s10660-025-10048-6

The impact of humans vs. AI recommendation on consumer reactions to products exposure

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Received: 16 January 2025 / Accepted: 23 September 2025

Abstract
This study compares consumer reactions to product recommendations provided by AI versus expert human agents for search and experience products. Across three experimental studies, we propose that the effect of recommendation source and product type on intention to follow the recommendation is explained by recommendation source's perceived transparency and credibility. We demonstrate that AI is perceived as more transparent and credible than a human expert when recommending search products, leading to a higher intention to follow the recommendation, while no difference emerges for experience products. However, when the human recommender is described as a *Super Expert* – highly experienced, reputable, and qualified – consumers show a preference for the human (vs. AI) source in the case of experience products, while the difference between the two recommendation sources became nonsignificant for search products. Furthermore, when recommendations come from a hybrid source combining a Super Expert and AI, this combination is evaluated less favorably than either source alone for search products, with no significant difference found for experience products. These results offer valuable insights for marketers on how to select, design and deploy effective touchpoints that enhance the willingness to follow recommendations, depending on the product type.

Keywords Product recommendations · Artificial intelligence · Human expert · Perceived transparency · Perceived credibility · Search products · Experience products

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Published online: 23 October 2025

1 Introduction

In today's highly digitalized retail environment, consumers often embark in complex and multi-touchpoint journeys before purchasing products [1]. Within such process, they are increasingly confronted with an overwhelming array of product and service options. This choice overload can sometimes impair decision quality and reduce motivation to choose [2–4]. To address this growing complexity and improve customer experience [5], companies often utilize artificial intelligence (AI) to support consumers' decision-making [3, 6–9]. AI has deeply changed the way consumers interact with brands along the decision journey, offering tools that personalize and streamline the shopping experience [10, 11]. Particularly, AI-powered recommendation systems are now widely used to help consumers identify relevant products and services, reduce cognitive load, and increase perceived value [12, 13]. Companies such as Amazon, Netflix and Spotify use AI and deep learning to monitor users' choices and provide recommendations that are often highly tailored to consumers' interests and shopping behaviors [6, 8, 14].

Consequently, a substantial body of research has investigated consumer responses to AI-generated recommendations in comparison to those offered by human agents, often adopting a binary perspective that positions AI and humans as mutually exclusive or opposing sources. Notably, prior studies have shown that consumers do not always prefer AI-generated reecommendations over those provided by humans. This phenomenon, known as "algorithm aversion" [15], suggests that consumers may perceive algorithms as incapable of handling subjective judgments or accounting for individual uniqueness [14, 16]. However, the effectiveness of AI versus human recommendation sources appears to be context-dependent [6, 16, 17]. Studies have demonstrated that AI is more accepted in rational or objective contexts, such as cognitive tasks [8] or numerical evaluations [16, 18]. One key contextual factor is product type [6, 8, 9, 19–23]. For example, consumers are more receptive to AI recommendations for search products – whose attributes can be evaluated before purchase – than for experience products – whose quality is assessed only after consumption [19, 20, 23–25].

Several mediating mechanisms have been proposed to explain the differential effectiveness of AI recommendations across search and experience products, including perceived effectiveness [23], credibility and usefulness [20], processing fluency and perceived service quality [19]. However, further research might be needed to deepen our understanding of the psychological mechanisms underlying consumer acceptance of AI versus human recommendations.

Recently, perceived transparency – defined as the extent to which a source is seen as open, clear, and complete [26–28] – has emerged as a relevant construct, particularly in contexts involving AI (e.g., [29]). Indeed, besides the positive impacts of interacting with AI in the customer journey, individuals may also face negative outcomes such as discomfort, uncertainty, and even fear [3]. These reactions are part of what has been described as the "dark side" of technology adoption, where feelings of reduced control over automated processes [30–32] and a lack of understanding about how the technology works [33–35] can foster threat perceptions and diminish trust. For more risk-averse individuals, algorithmic decision-making may be perceived as

especially vulnerable to negative outcomes due to the opacity of underlying processes [36], a concern exacerbated by firms' limited transparency regarding data usage [37]. In light of these potential drawbacks, understanding consumers' perception of transparency of AI-based recommendation agents seems to be particularly crucial.

Differences in how AI and human agents generate and communicate information may strongly influence perceived transparency and, consequently, consumers' perceptions of reliability and completeness [38]. Moreover, transparency is increasingly conceptualized as an antecedent of credibility [29, 39, 40], which refers to the extent to which a recommender is seen as knowledgeable and trustworthy [41–44]. Since prior work has shown that perceived credibility mediates the relationship between recommendation source (AI vs. human) and consumers' acceptance of the recommendation [20], perceived transparency and perceived credibility may operate as sequential mediators in shaping consumer responses. Building on this theoretical foundation, the present research aims to investigate the joint effects of recommendation source (AI vs. human) and product type (search vs. experience) on consumer responses, while testing the sequential mediating roles of perceived transparency and perceived credibility.

Within this framework, two additional factors deserve further scholarly attention. On the one hand, whether and how the level of product expertise of the human recommender – a critical factor for managers when designing their touchpoint portfolio [45] – affects consumers perceptions and behavioral intentions toward recommendations offered by humans vs. AI has remained largely overlooked. This is a notable gap, considering the well-established impact of product expertise on consumer decision-making (e.g., [46–48]). Ignoring this variable risks oversimplifying the nuances in the relationship between AI and human and may trigger misleading conclusions about the relative effectiveness of such recommendations sources. It could be possible, for instance, that the perceived effectiveness of the human recommender vis-à-vis AI might be contingent upon how expert he/she is perceived by consumers.

On the other hand, while the bulk of previous research has compared the perceived effectiveness of product recommendations offered by human vs. AI agents, an emerging area of inquiry lies in the combination of human and AI as recommendation sources [6, 9, 49]. This hybrid approach reflects a growing trend among organizations to leverage the complementary strengths of both humans and AI in their recommendation systems. However, despite its increasing practical relevance, consumer responses to such integrated recommendation sources remain largely unexplored. Understanding how consumers perceive and react to these hybrid models is crucial for advancing theory and providing actionable insights for businesses. Early evidence suggests that these models can improve consumer responses in specific contexts – such as utilitarian vs. hedonic products [6] or virtue vs. vice framing [9]. We extend this knowledge in two key ways. First, by investigating how consumers react when facing search vs. experience goods. Second, by exploring the underlying role of perceived transparency, and credibility as mechanisms explaining why different types of recommendation sources (human, AI or a "hybrid" combination of both) might affect intention to follow the recommendation.

Building on the above objectives, our research seeks to answer the following questions:

RQ1: How do different recommendation sources (AI alone, human alone, or the combination AI + human) influence consumers' intention to follow a recommendation?

RQ2: Do perceived transparency and credibility sequentially mediate the relationship between recommendation source and consumer response?

RQ3: How do these effects vary depending on product type (search vs. experience) and the level of expertise of the human recommender?

Overall, this study makes three primary contributions to the literature. First, we propose and empirically test a sequential mediation model in which the recommendation source (human agent vs. AI vs. a combination of both) is predicted to affect perceived transparency and, in turn, perceived credibility and consumers' intention to follow the recommendation. We examine how this mechanism varies depending on product type (search vs. experience), to better understand when and why different recommendation sources are more effective. By doing so, we aim to shed light on novel psychological mechanisms explaining consumer reactions to recommendations offered by human-based vs. AI-based sources. Second, we incorporate the level of product expertise of the human recommender in our analysis. By doing so, we aim to shed light the to-date untested role of human recommenders' expertise in shaping the effectiveness of human-based vs. AI-based product recommendations. Third, we compare single recommendation sources to the case in which the recommendation is provided by both the AI and a human agent to make our comparative analysis more complete. Our research also bears relevant implications for marketing managers interested in maximizing the effectiveness of recommendation sources for different types of products.

2 Theoretical background and hypothesis development

2.1 Recommendation source: AI versus human recommenders

In their processes of active evaluation of product alternatives [50], consumers are used to listening to advice and recommendations from others who own or have used a particular product, have the expertise to make credible judgments [51] and are reliable sources of product information [52]. However, in recent years, AI advisors have emerged as an additional source of recommendations that may better align with consumers' needs [6, 8, 53] compared to human recommenders.

AI recommendations are typically generated by algorithms – computer systems that use rule-based or machine learning methods to produce outputs (Jussupow et al., 2020). These systems have demonstrated superior performance compared to humans in several domains. For example, algorithms outperform professionals in medical diagnoses [54], and even in subjective tasks such as predicting how funny a joke will be [55]. While algorithms can support better-informed decision-making [56], their effectiveness depends heavily on whether consumers are willing to accept their advice [14, 16, 57].

Scholars have been tackling this issue, and several studies comparing the effectiveness of human versus AI recommendation sources have been produced [6–9, 21, 58]. Interestingly, however, previous research suggests that consumers often resist

algorithmic advice [14, 15]). For instance, they frequently prefer human forecasters over statistical algorithms, even when the algorithm performs better – a pattern observed whether the human forecaster is another person or themselves [15]. Similar resistance appears in various domains: employees reject algorithmic input in product assortment decisions [59],rideshare drivers ignore algorithmic routing when it contradicts their own experience or peer behavior [60],patients favor physicians who do not rely on AI, even when AI-based recommendations are proven to be more accurate [14]. Professionals are not immune either, as similar reluctance to follow AI advice has been found in expert contexts [61]. Further compounding the issue, consumers may experience increased uncertainty when receiving AI-generated recommendations, especially in purchasing decisions [3]. Additionally, [62] show that consumers' lay beliefs influence their receptivity: shifting from the assumption that "AI excels at objective tasks" and "humans at subjective tasks" to the reverse can alter preferences toward AI vs. human recommenders. Consumers' willingness to engage with AI also varies based on the relationship context. For example, consumers are less likely to use AI tools when selecting gifts for close friends – compared to casual acquaintances – because they doubt AI's ability to match preferences and communicate relational meaning [63].

Nevertheless, other studies have highlighted that more favorable consumer responses to AI are possible, for instance by making consumers believe they can get an explanation about how the algorithm works [64], by giving consumers some control over it [15] or when individuals think that, due to external factors (i.e., God), human judgment is imperfect [65]. Still, consumers might feel less judged by AI rather than by humans [66]. This is especially true in situations involving embarrassment or self-presentation concerns: consumers feel less judged by robots than by humans when having to engage in an embarrassing service encounter [67], and less embarrassed when interacting with chatbots in contexts where self-presentation matters, due to the lower mind ascribed to AI agents [68]. Moreover, consumers might prefer interacting with AI for objective (vs. subjective) tasks [16], when they needs are certain [23], in the utilitarian (vs. hedonic) context [6, 8] and when recommendation agents are anthropomorphized [69] or socially present [20]. Addittionally, consumers attribute less prejudicial motivations to algorithms, which makes them feel less morally outraged by algorithmic (vs. human) discrimination [70].

Finally, [71] suggest that enjoyment in interacting with technology can positively influence consumers to take action, such as disclosing personal information.

These seemingly contradictory findings suggest that the effectiveness of AI-based versus human recommendations might be highly context-dependent. This is particularly evident across different product categories [6, 8, 9, 21, 22, 72]. A widely used framework in this area distinguishes between search products and experience products [24]. [23], for example, found that consumers with stronger preference certainty were more inclined to interact with AI (e.g., chatbots) during the pre-purchase stage, but only for search products. Similarly, [20] showed that voice-based AI recommendations were more persuasive than text-based online reviews, particularly for search products, and that factors such as the AI's voice gender also influenced consumer response. More recently, [19] observed a matching effect between chatbot and human service efficacy depending on product type, with chatbots outperforming humans

for search products. Further research also shows that AI is generally viewed more favorably when recommending utilitarian rather than hedonic products [6, 8], functional rather than symbolic products [21, 22], material rather than experiential products [72] and virtue over vice products [9]. Collectively, these findings underscore the critical role of context in shaping the effectiveness of AI-generated vs. human recommendations.

2.2 Perceived transparency and perceived credibility

While people are open to consulting algorithms, they often exhibit hesitation or reluctance when it comes to actually adopting algorithmic recommendations [15, 16, 57]. Rohden and Espartel [3] found that, despite the potential benefits of AI in enhancing the customer journey, consumers report heightened uncertainty about their purchase decisions when receiving product recommendations from AI. Although this study did not directly examine perceived transparency, the authors highlight that this uncertainty may stem from a perceived loss of control over automated processes [30–32] and from limited understanding of how AI operates [33–35]. These factors underscore consumers' difficulty in grasping the rationale behind AI-generated recommendations, underscoring the potential role of perceived transparency in shaping consumer responses.

Consumers are increasingly confronted with overwhelming volumes of information during their decision-making processes, which can lead to complex decision loops [73] and may consequently increase their sensitivity to the perceived transparency of information sources. According to Parris et al. [27], transparency is shaped by the degree to which organizations share information openly. In this context, transparency refers to the extent to which an entity discloses details about its decision-making processes, operations, and performance – including relevant aspects of the products or services being recommended [74].

In the domain of AI versus human recommendations, a recurring concern among consumers is that AI systems often function as "black boxes," offering little insight into the rationale behind their recommendations [29, 75–77]. As a result, algorithmic advice is frequently perceived as impersonal, rigid, and poorly attuned to individual needs or contextual nuances [14]. When algorithms fail to provide explanations or display insufficient contextual awareness, users may respond with skepticism and distrust [78], similar to their reaction to unsolicited advice from unfamiliar individuals [79, 80]. The opacity of algorithmic decision-making mechanisms thus contributes to a general aversion toward AI-generated advice [75, 81].

Indeed, a stream of research suggests that providing users with evidence of algorithmic transparency with meaningful information about how the algorithm functions can improve attitudes toward algorithmic recommendations [75, 76]. For example, a field study by Kawaguchi [59] found that workers were more likely to comply with algorithmic instructions when they had some understanding of the algorithm's underlying logic. Similarly, [81] observed that decision-makers responded more positively when the principles behind the algorithms they used were made transparent. These findings suggest that perceived transparency might play a crucial role in fostering acceptance of algorithmic advice.

Although several studies have begun to examine the effects of transparency (e.g., [55, 77, 81]), the mechanisms through which transparency promotes the adoption of algorithmic (vs. human) advice remain underexplored.

We fill this gap by arguing that perceived transparency shapes intention to follow the recommendation via perceived credibility of the source. Perceived credibility can be described as the extent to which a recommender is seen as possessing domain-relevant expertise and being trustworthy in delivering objective information [43]. Recent research has started to shed an initial light on this relationship. For instance, [29] found that algorithmic transparency affects users' reliance on AI advice via different trust-related beliefs (i.e., competence, integrity, and benevolence), offering preliminary evidence of a link between transparency and credibility in algorithmic contexts. Additional support comes from [40] and [39], who, albeit in different domains, found that transparency positively influences perceived credibility [40], for example, showed that credibility mediates the relationship between perceived transparency and perceived ethicality, while [39] identified credibility as a key component in the broader conceptual framework of transparency. However, despite these emerging insights, no prior research has directly tested whether—and how—perceived transparency drives perceived credibility in the context of AI versus human recommendations. Our work fills this important theoretical gap.

Research on credibility has drawn extensively from communication, psychology, sociology, and marketing [82], and consistently suggests that credibility is a critical factor in consumer decision-making. Consumers place high importance on the perceived credibility of an information source [83] and are significantly less likely to follow product recommendations from sources they perceive as lacking credibility [20, 84]. Moreover, perceived credibility strongly influences behavioral intentions, such as whether to adopt a recommendation, purchase a product, or recommend it themselves to others [20, 41, 42, 44].

This mediating role of credibility is particularly relevant in the context of both human and technological recommenders. For instance, [85] showed that the influence of recommendations – whether generated through blockchain technology or based on expert judgment – on consumer behavioral intentions is mediated by perceptions of the information provider's credibility. These findings underscore the central role of perceived credibility as a factor possibly explaining why transparency affects consumer intention to follow the product recommendations.

2.3 Level of expertise

Expertise is a cognitive attribute that refers to the skills, knowledge, and experience possessed by an individual [86]. Since the early development in communication theory, human expertise has been recognized as a key factor influencing consumer responses [43, 46, 87, 88]. Numerous studies have shown that when endorsers or recommenders are perceived as experts, their advice tends to be more persuasive and more likely to be accepted by consumers [45, 86]. For instance, a celebrity endorser with high perceived expertise is generally more influential than one perceived to have low expertise [43, 89]. This effect is particularly salient in product categories that

require technical knowledge, such as high-tech goods, where expert recommenders are found to have a stronger persuasive impact [47].

Within the growing literature comparing AI and human recommendation agents, the role of perceived expertise has emerged as a key factor in shaping user responses. [18] argue that consumers' reactions to algorithmic recommendations – whether favorable or resistant – are often contingent on the perceived level of expertise of the human alternative. Supporting this notion, [90] conducted a meta-analysis of studies contrasting algorithmic and human sources, revealing a consistent pattern: algorithm aversion was more likely to emerge when the human agent was described as highly competent (e.g., a doctor or domain expert). Conversely, algorithm appreciation tended to surface when the human alternative was vaguely described, such as "other participants" or "unspecified people." These findings suggest that the framing of human expertise critically shapes the perceived value of algorithmic advice. In essence, consumers may be more inclined to trust algorithms when the human comparator lacks clear expertise, and more likely to resist algorithmic input when the human source is portrayed as knowledgeable and experienced [90].

2.4 AI-human hybrid recommenders

In some contexts, it is likely that AI is not replacing the human intelligence, but it has a complementary role [6, 91]. An AI-human hybrid decision-making model integrates the intelligence of humans and AI to seemingly offer more complete product recommendations.

Research suggests that this hybrid approach can be valuable in decisions that are considered relevant [92] and might mitigate consumer resistance to AI. [72] found that when AI is positioned as a supportive assistant rather than a replacement for a human expert, consumers no longer perceive AI recommendations as less competent than human ones in the context of experiential products – suggesting a synergistic effect that surpasses the impact of either source alone. Similarly, [6] discovered that the word-of-machine effect – the phenomenon by which consumers tend to prefer AI-driven recommendations for utilitarian (vs. hedonic) products rather than human recommendations – is eliminated when AI is framed not just as "artificial" intelligence but as a human-AI hybrid system. In other words, the human decision maker is likely to compensate for the negative effects associated with AI in several cases, such as when the recommended product owns subjective or experiential attributes [6, 72]. In another study, [49] found that the combination of AI and a seller in the case of second-hand trading on P2P platform can work better than the seller alone and at the same level of AI in increasing customers' perceived objectivity and willingness to pay. Recently, Yang et al. [9] have demonstrated that an hybrid source composed by AI and human (vs. AI only) can improve consumer responses to vice (vs. virtue) frame products.

These findings suggest that the human-AI hybrid source can elicit more positive consumer responses by leveraging the complementary strengths of both agents. However, an important caveat remains largely unexplored: the potential ambiguity surrounding the roles played by the human and the AI in generating the recommendation. In many hybrid decision-making contexts, the contribution, the interplay, the

sequence, and the role of AI and the human agent in providing the final recommendation (e.g., whether the AI provides the initial analysis and the human refines it, or vice versa) might not be always clear to consumers. This lack of clarity may reduce perceived transparency, undermining consumer trust.

Literature on customer confusion highlights that when consumers are exposed to multiple or indistinct sources of information, they may experience cognitive overload and decision paralysis [93–96]. If the hybrid recommendation source is not sufficiently transparent about the relative roles of human and AI, consumers, we argue, may feel disoriented or skeptical, ultimately weakening their intention to follow the recommendation.

2.5 Hypotheses development

During an online shopping journey, consumers need sufficient information about products or services to make satisfactory and informed purchase decisions [97]. AI can play a significant role in assisting consumers with search products, given its superior cognitive capabilities for providing accurate information about product characteristics [98, 99]. According to "mind perception theory" [100], people evaluate AI and human mental abilities along two complementary dimensions: agency – encompassing planning, memory, and computation related to thinking and execution [101] – and experience – encompassing sensations such as desire, hunger, pain, and pleasure, related to mental states of feeling [100]. AI is often perceived as better suited for providing fact-based evaluations, logic, and rationality [7, 98], which are crucial for assessing search products. Search products typically have standardized attributes, low variability, and can be assessed quantitatively using instrumental cues [7]. Consequently, consumers may view AI as particularly useful at evaluating whether a product meets their specific needs through detailed technical analysis, leading them to perceive AI as a more transparent and credible source of recommendations. However, this does not apply to experience products, which require consumers to try or purchase them to form a reliable judgment [23, 24, 102]. In these cases, consumers may feel that AI, which cannot directly experience the product, is less equipped to provide the same level of support provided for search products [98]. Therefore, for experience products, AI may be perceived as less capable of offering comprehensive and reliable (transparent) recommendations compared to human experts, similar to the perception of hedonic products [8, 18]. It is important, however, to distinguish between hedonic products, which provide multisensory benefits and are purchased for pleasure-related outcomes [8, 103], and experience products, which do not necessarily involve sensory pleasure but have attributes that can only be evaluated after experiencing them [104].

Therefore, it is possible that for experience products preference for AI recommendations may be less strong than for search products, and thus no difference in consumer reactions to recommendations provided by humans versus AI might manifest. Formally, we hypothesize the following:

H1 *For search products, consumers perceive AI as more transparent and credible than human experts, leading them to be more likely to follow AI recommendations. For experience products, this difference is less likely to be observed.*

Our core assumption is that AI (as opposed to a human) functions as a more effective recommendation source for search products compared to experience products, primarily due to higher perceptions of transparency and credibility associated with AI. Building on this premise, we investigate whether these effects can change when introducing changes in the recommendation sources. Specifically, we explore two potential boundary conditions: (1) when AI is evaluated against a highly knowledgeable human agent – hereafter referred to as a Super Expert to distinguish them from an ordinary expert – and (2) when AI is presented in combination with the Super Expert, forming a hybrid human–AI recommendation source. These conditions allow us to examine how variations in human expertise and the integration of AI with human intelligence may influence consumers' responses across product types, potentially offering a more nuanced view of the effectiveness of different types of recommendation sources on consumers' reactions for different product types.

While little research has examined how perceived expertise may influence perceptions of transparency, there are reasons to believe that the level of perceived expertise of the product recommender could positively affect perceived transparency. Specifically, consumers may intuitively infer that a highly expert human recommender – thanks to its experience, past track record, reasoning skills, and ability to understand subtle contextual cues – is more capable of explaining recommendations in a clear and relatable manner. Super Experts are in fact individuals who possess—or claim to possess—a superior depth or breadth of knowledge within a specific domain, supported by a proven track record. This expertise enhances their ability to generate new insights in response to domain-specific questions [105]. In this regard, the perceived expertise of the source significantly amplifies the impact of the message conveyed [106].

In contrast, while algorithmic agents are often seen as objective and data-driven, they may lack the capacity to illustrate the rationale behind their suggestions in a way that feels personalized or context-sensitive, particularly in the case of experience products. This perceived gap in explanatory power may, in turn, influence users' judgments of transparency and ultimately shape their willingness to accept the recommendation [107].

Drawing on research suggesting that a highly competent and experienced advisor is generally believed to be more persuasive than an advisor with low perceived experience [86] and that the consumers react more positively to recommendations provided by humans known to be particularly expert [87, 108], we predict that, especially for experience products, perceived source transparency and credibility and, in turn, intention to follow the recommendation, will be higher when the recommender is a highly experienced and reputed human agent rather than AI. Formally:

H2 *When a human recommender is highly knowledgeable about the product, consumers will see him/her as more transparent and credible than AI, leading to a higher intention to follow the expert human's recommendation for experience products.*

Despite a growing body of research on the AI-human hybrid decision-making model (e.g., [6, 9, 49, 72]), little is known about how the use of an hybrid recommendation source intelligence influences perceived transparency. Building on the research discussed so far, the involvement of a human may help make the AI's recommendations more interpretable and reassuring, thus making the human-AI hybrid source more effective [6, 9, 49, 72]. However, recent findings by Bian et al. [109] suggest that combining human and AI sources may not always produce additive benefits. Their study challenges the assumption that multiple sources inherently enhance communication effectiveness. Indeed, while diverse inputs may appear beneficial, information overload can backfire, especially in peculiar and pontentially stressful contexts as disaster warnings, where integrating AI and human expert input resulted in a crowding-out effect, resulting in the combined source to be less effective than single sources on its own [109].

Consumers may experience greater doubt and confusion – rather than increased clarity – when they receive input from multiple channels (Ball & Wozniak, 2022) or when the volume of information exceeds their cognitive capacity, resulting in overload [110]. In such cases, they may blame companies for creating an overly complex decision environment, question the company's motives, and struggle to build trust in individual products. Although greater informational transparency is often appreciated, an excess of input can become counterproductive, triggering dissatisfaction and negative evaluations of the company [110]. Confusion is a cognitively taxing and negatively valenced emotional state – consumers simply do not like feeling confused. As such, it can result in unfavorable judgments toward both the product and the company behind it [111].

In line with this reasoning, we propose that dual agents may introduce ambiguity regarding the origin and credibility of the recommendation [93, 96]. When the roles of human and AI agents are not clearly defined, as well as the sequencing of information they provide, the perceived transparency of the recommendation process may be undermined.

This potential downside of hybrid recommendation sources may be particularly pronounced in the case of search products. For these products, consumers are generally able to gather and evaluate information independently before making a purchase [24, 25]. When recommendation come from both a human and an AI agent – even if presented as a single output – and the consumer already possesses or seeks out product-related knowledge, the number of informational sources effectively triples. This may lead to information overload, increasing cognitive burden and ultimately reducing perceived transparency due to the difficulty in integrating multiple inputs. In contrast, for experience products, that can only be evalueted after consumption [19, 20, 23–25], consumers lack the ability to independently verify information beforehand. As a result, the combination of AI and human input may still present some risk of confusion, but the likelihood of cognitive overload is lower due to the reduced number of information sources involved and consumers' eagerness to increase their perceived ability of advance verification. Therefore, the negative impact of hybrid recommendation sources on perceived transparency is expected to be stronger for search products than for experience products. Therefore, we hypothesize the following:

H3 *When the recommendation is made through a combination of AI and the Super Expert, consumers will see this AI-human hybrid recommendation source as less transparent than AI and the Super Expert alone, leading to a lower intention to follow the recommendation for search products.*

3 Overview of studies

We tested our hypotheses across three studies by using the same operationalization of consumer responses (perceived transparency, perceived credibility, and intention to follow the recommendation) and categorization of products (search and experience), but with different manipulations of the recommendation source. In Study 1 we tested consumer responses to a recommendation provided by AI versus a human "standard" expert. In Study 2 we tested if consumer responses change if the human recommender is presented to be a highly experienced, reputed and qualified expert. Finally, in Study 3, we tested if consumer responses change if the recommendation is derived from AI technology integrated with insights from the highly experienced, reputed and qualified expert.

A summary of the studies is provided in Table 1, and the conceptual model is presented in Fig. 1.

Table 1 Summary of research designs and finding

Studies	Samples	Experimental Designs	Other variables
Study 1	Prolific users (N = 485)	2 (Recommendation source: AI vs. Expert) × 2 (Product type: Search vs Experience) between-subject design	• M_1: Perceived transparency • M_2: Perceived credibility • DV: Intention to follow the recommendation
Study 2	Prolific users (N = 247)	2 (Recommendation source: AI vs. Super expert) × 2 (Product type: Search vs Experience) between-subject design	• M_1: Perceived transparency • M_2: Perceived credibility • DV: Intention to follow the recommendation
Study 3	Prolific users (N = 293)	3 (Recommendation source: AI vs. Super expert vs. Super expert combined with AI) × 2 (Product type: Search vs Experience) between-subject design	• M_1: Perceived transparency • M_2: Perceived credibility • DV: Intention to follow the recommendation

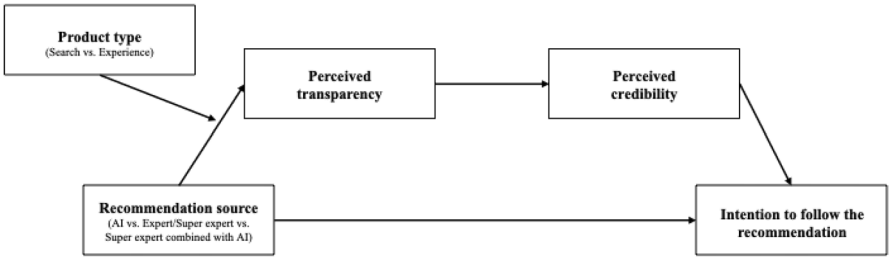


Fig. 1 Conceptual Model

4 Study 1

4.1 Method

Four hundred eighty-five individuals (M_{age} = 42.63 years, SD = 14.30, 35.7% male) from the US and UK were recruited via Prolific and participated in the between-subjects study in exchange for payment. They all successfully passed the attention check and demonstrated active understanding and recall of the stimulus they were exposed to. At the end of the experiment, participants were informed that the product and information used in the study were fictitious.

After a brief introduction, respondents were randomly exposed to one of the four experimental conditions: AI product recommendations (N_{Search} = 108; $N_{Experience}$ = 145) versus human product recommendations (N_{Search} = 122; $N_{Experience}$ = 110). We gave participants the following instruction: "Please read the following part carefully and observe the pictures. Imagine that you need to purchase a Notebook/Virtual Reality Headset in your online store and find the product below. As displayed, the website employs a cutting-edge Artificial Intelligence (AI) solution/set of industry experts to recommend a product as well matched as possible to customer preferences." Then, they were asked to answer questions measuring the core outcome variables: perceived transparency was assessed using a 7-point Likert scale (1 = strongly disagree; 7 = strongly agree [112, 113], perceived credibility was assessed using a 7-point semantic differential scale tested by [43], and intention to follow the recommendation was assessed using a 7-point Likert scale (1 = strongly disagree; 7 = strongly agree) already adopted by [14] – see Web Appendix, Table 6 for measurement scales. In the latter case, we assessed participants' willingness to follow the recommendation with a single item, as done in previous research [14, 32], since it is appropriate when a doubly concrete construct – that is, one that has a simple, clear object (e.g., a recommendation) and a single attribute with a single meaning (e.g., intention to follow the recommendation) – is involved [114].

All items highlight a high level of reliability and validity with all factor loadings exceeding the suggested cut-off of 0.70 [115]. The convergent validity suggests that all loadings measure the construct properly (Loading > 0.70 and squared multiple correlations [SMC] > 0.50) while remaining distinctive among them as the average variance extracted is higher than SMC (see Web Appendix – Table 8). The analysis confirms that the AVE values exceed the corresponding correlations, thereby support-

ing the discriminant validity of the constructs (see Web Appendix – Table 9) suggesting that the discriminant validity has been established and that our measures are able to discriminate the constructs under measurement [116].

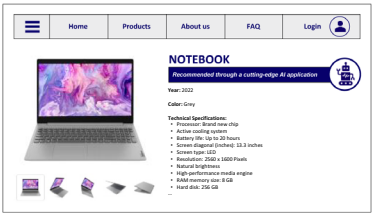
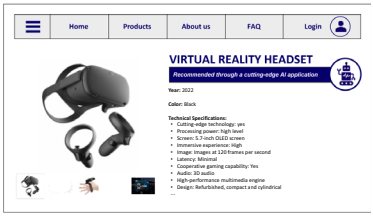
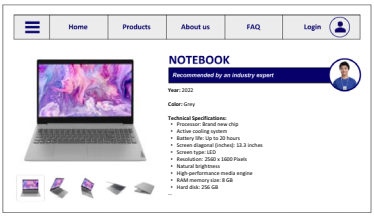
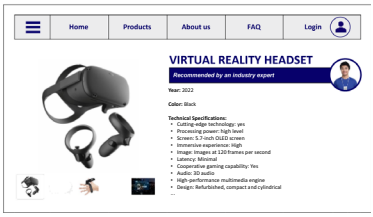
The stimuli used in the experiment were inspired by MediaMarkt [117], a German electronics and consumer appliance chain. The interface and graphics were slightly changed for purposes of the study (see Table 2). Participants saw an image displaying and describing either a notebook or a virtual reality headset recommended by AI or a human expert.

We selected our products after performing a pretest among 80 individuals (M_{Age} = 32.38 years, SD = 11.71, 46.3% male) recruited through Prolific in exchange for payment. Respondents were provided with the definition of search and experience products [25], where "search products are identified as those whose relevant attribute information can be easily obtained prior to use/purchase", and "experience products are those whose relevant attribute information cannot be known until the trial/use of the product/service" [25]. We then asked them to assign ten products to the "search" or "experience" category. Results revealed that "notebook," "bluetooth speaker," and "smartwatch" were perceived to be nearly equal search products, thus we then decided to use the former,whereas the most frequently cited experience product was a "virtual reality headset" (see Web Appendix – Table 7.

4.2 Results

A one-way analysis of variance (ANOVA) assessed differences in perceived transparency, perceived credibility, and intention to follow the recommendation of AI versus a human expert. ANOVAs revealed a significant effect of Recommendation source on Perceived transparency (M_{AI} = 4.74, SD = 1.13 vs. M_{Expert} = 4.52, SD = 1.12, F(1, 484) = 4.50, p = .009), Perceived credibility (M_{AI} = 4.72, SD = 1.07 vs. M_{Expert} = 4.91, SD = 1.03, F(1, 484) = 3.98, p = .008), and Intention to follow the recommendation (M_{AI} = 4.44, SD = 1.23 vs. M_{Expert} = 4.19, SD = 1.29, F(1, 484) = 4.39, p = .009).

Table 2 Study 1: Stimuli and experimental conditions

	Search product	Experience product
AI condition		
Expert condition		

To assess the overall indirect effect of Recommendation source and Product type on Intention to follow the recommendation through Perceived transparency and Perceived credibility, we conducted a regression analysis via PROCESS (Model 83 – [118]) with Recommendation source (Expert = 0,AI = 1) as the independent variable and Product type (Experience = 0; Search = 1) as moderator. Perceived transparency and Perceived credibility were the mediators, and Intention to follow the recommendation was the dependent variable. Analysis revealed a significant effect of recommendation source on Perceived transparency (b = 1.151, $p < .001$) and a significant effect of Perceived transparency on Perceived credibility (b = .698, $p < .001$), which significantly affected the Intention to follow the recommendation (b = .369, $p < .001$). Additionally, a significant interaction between Recommendation source and Product type on Perceived transparency (b = -.623; $p = .002$) emerged. Participants perceived AI as more transparent for the Search product ($M_{AI} = 4.83$, SD = 1.04 vs. $M_{human} = 4.30$, SD = 1.13, b = .528, $p < .001$), while no significant difference between the two recommendation sources appeared for the Experience product ($p = .500$; Fig. 2 and Fig. 3).

We also obtained a significant index of moderated mediation through Perceived transparency and Perceived credibility (b = -.160; LCI = -.283; UCI = -.056). Results showed that the indirect effect of Recommendation source on Intention to follow the recommendation through Perceived transparency and Perceived credibility was not fully significant for the Experience product (b = -.024; LCI = -.097; UCI = .052). However, the indirect effect was significant for the Search product (b = .136; LCI = .056; UCI = .232), indicating that Perceived transparency and Perceived credibility sequentially mediated the effect of Recommendation sources on Intention to follow the recommendation. Figure 4 summarizes these results.

As a further investigation, we also explored whether other, simpler models could have been viable and more appropriate. To this end, we conducted a comparison using Structural Equation Modeling. The results suggest that the moderated serial mediation model was the only one that reached acceptable levels for the cut-off criteria of GFI, CFI, NFI, RMSEA, and SRMR, indicating a good fit with the sample data [119]. The other tested models did not meet the suggested cut-off thresholds. (see Table 3).

4.3 Discussion

Study 1 offers initial support for our proposed sequential mediation model, confirming H1. Specifically, the results show that the impact of the recommendation source on consumers' intention to follow the advice is mediated by perceived transparency and perceived credibility. Interestingly, although human recommenders were initially rated as more credible overall, consumers still reported a higher intention to follow AI-based recommendations. This apparent asymmetry can be explained by the fact that AI sources were perceived as more transparent – an upstream factor in our mediation model that directly influences perceived credibility.

Also, the effect of the recommendation source on consumers' intentions critically depends on the type of product. For search products, an AI-based recommendation was perceived as more transparent and credible than a recommendation provided by a

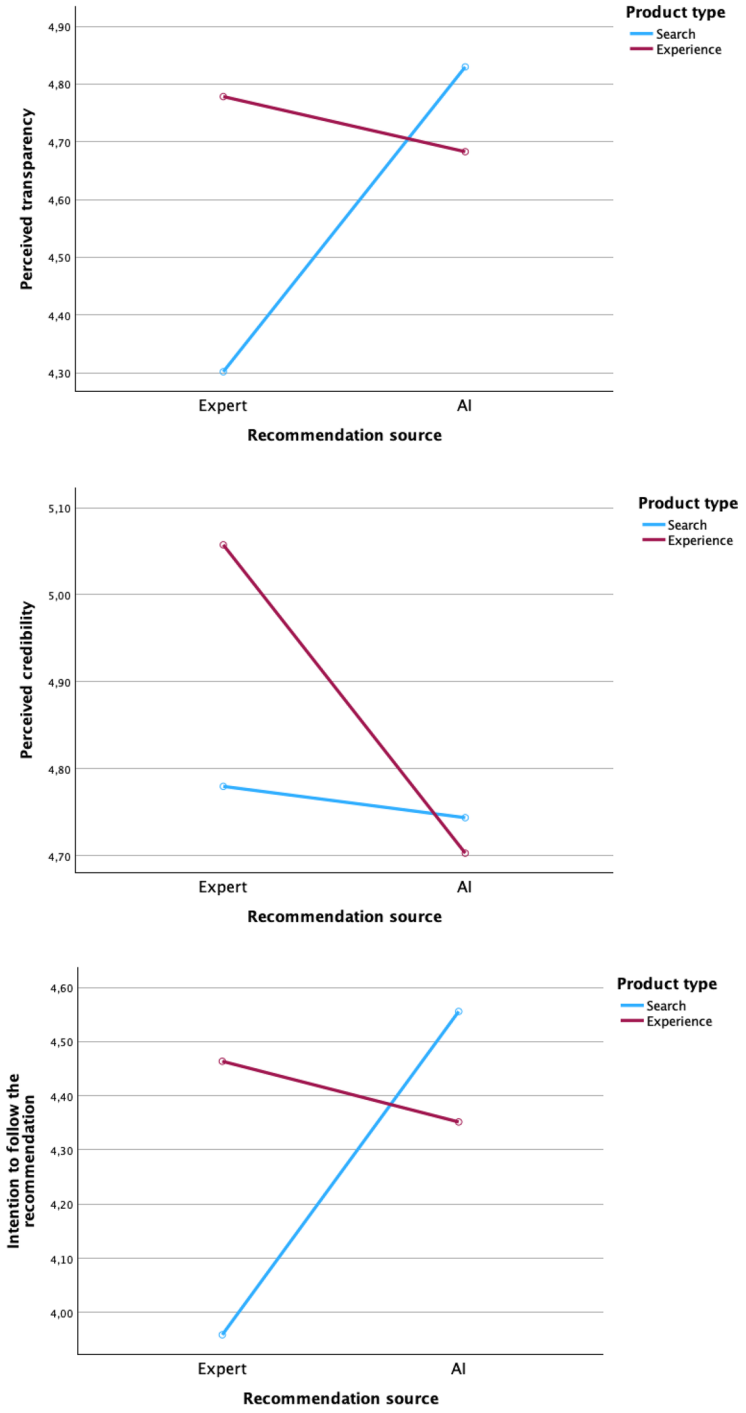


Fig. 2 Study 1: Interaction between Recommendation source (AI vs. Expert) and Product type (Search vs. Experience) on Perceived transparency, Perceived credibility, Intention to follow the recommendation

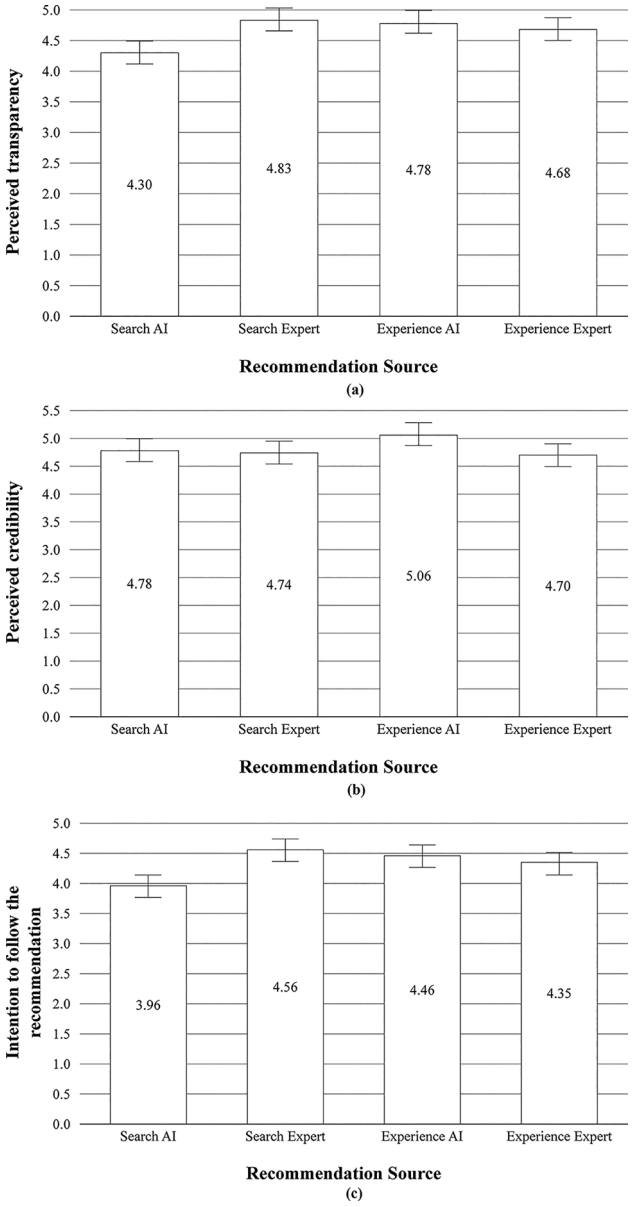


Fig. 3 Study 1: Bar Graphs with Standard Errors Bars (95% C.I.) by Perceived transparency, Perceived credibility, Intention to follow the recommendation

human source, leading to a higher intention to follow the recommendation. However, this difference did not manifest for experience products.

While these findings confirm our core assumption, at the same time, they raise the question of whether the effects observed are robust when the changing the human

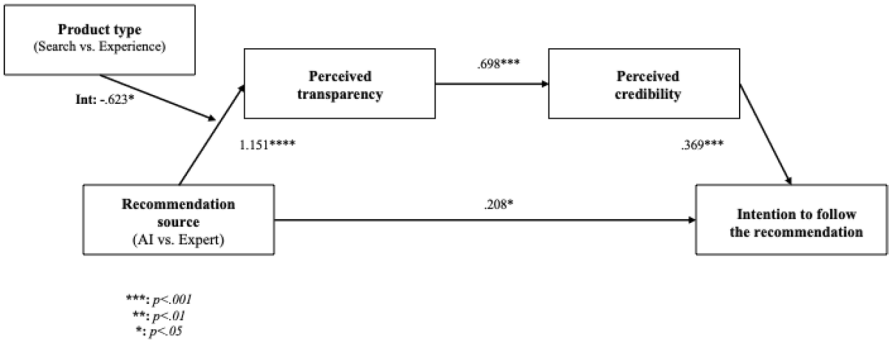


Fig. 4 Study 1: Results

Table 3 Results of Structural Equation Modeling—Indices of Goodness of Fit

Model	$\chi 2$	df	CFI	NFI	RMSEA	SRMR
Recommendation source (AI vs. Expert)—> Product type (Moderator)—> Intention to follow the recommendation	854.015	0.707	0.301	0.304	1.328	0.397
Recommendation source (AI vs. Expert)—> Product type (Moderator)—> Perceived transparency (Mediator)—> Intention to follow the recommendation	879.039	0.797	0.653	0.651	0.386	0.196
Recommendation source (AI vs. Expert)—> Product type (Moderator)—> Perceived credibility (Mediator)—> Intention to follow the recommendation	1014.777	0.796	0.716	0.711	0.258	0.132
Recommendation source (AI vs. Expert)—> Product type (Moderator)—> Perceived transparency (Mediator)—> Perceived credibility (Mediator)—> Intention to follow the recommendation	324.721	0.906	0.944	0.928	0.074	0.060

recommender. We address this issue in Study 2 by investigating whether and how these results change if the human recommender is presented as a "super expert".

5 Study 2

5.1 Method

Two hundred forty-seven individuals (M_{Age} = 38.69 years, SD = 10.99, 35.6% male) were recruited via Prolific and participated in the between-subjects study for a monetary reward. They all successfully passed the attention check and demonstrated active understanding and recall of the stimulus they were exposed to.

The study design was the same as in Study 1. We only varied the manipulation of the human recommender condition. While in Study 1 we had a "standard" human Expert, in Study 2 we had a Super expert. Practically, we developed our manipulation by leveraging on the Cochran-Weiss-Shanteau's approach [120], in which we

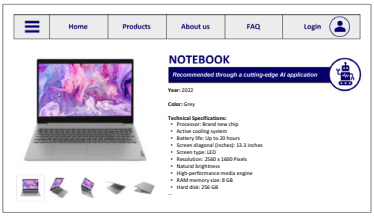
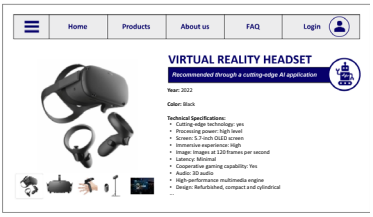
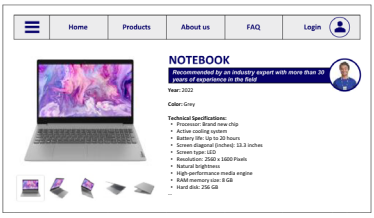
described the human recommender as someone who had more than 30 years of experience in the field, had obtained official certifications, had acquired a solid education through practical experiences and individual studies during his career, was recognized as an authority in the field and had received numerous awards. We conducted a pretest with 80 respondents (M_{Age} = 36.05 years, SD = 12.12, 28.7% male), which confirmed that the Super expert was perceived as more expert than the "standard expert" used in Study 1 ($M_{Super\ expert}$ = 6.29; SD = 0.99 vs. M_{Expert} = 5.58; SD = 0.95; F(1,79) = 9,758, p < .01).

Subsequently, participants were randomly exposed to one of the four experimental conditions: AI product recommendations (N_{Search} = 59; $N_{Experience}$ = 64) versus Super expert human product recommendations (N_{Search} = 54; $N_{Experience}$ = 70) (see Table 4). Then, they were asked to answer the same questions as in Study 1 (see Web Appendix – Tables 8 and 9 for the measures of reliability and validity).

5.2 Results

The ANOVAs highlighted a significant effect of Recommendation source on Perceived transparency (M_{AI} = 4.82, SD = 0.86 vs. $M_{Super\ expert}$ = 5.40, SD = 0.90, F(1, 246) = 26.101, p < .001), Perceived credibility (M_{AI} = 4.68, SD = 0.96 vs. $M_{Super\ expert}$ = 5.82, SD = 0.80, F(1, 246) = 101.492, p < .001), and Intention to follow the recommendation (M_{AI} = 4.39, SD = 1.19 vs. $M_{Super\ expert}$ = 5.04, SD = 1.09, F(1, 246) = 19.851, p < .001). Thus, unlike Study 1, respondents perceived the Super Expert human recommender as more transparent and credible than AI, resulting in a higher Intention to follow his/her recommendation.

Table 4 Study 2: Stimuli and experimental conditions

	Search product	Experience product
AI condition		
Super expert condition		

Description of Super expert condition:"The expert has more than 30 years of experience in the field. He has obtained official certifications in the specific field and has acquired a solid education through practical experiences and individual studies during his more than 30-year career. Currently, he is recognized as an authority in the field by other experts and has received numerous awards and recognition for his influence in the field. He is reliable, timely and delivers accurate and informed recommendations."

In addition, we performed a regression analysis via PROCESS (Model 83 – [118]) to assess the moderating effect of Product type on Perceived transparency, with Recommendation source (Super expert = 0; AI = 1) as the independent variable, Product type as the moderator (Experience = 0; Search = 1), and Perceived transparency as the dependent variable.

We found a significant interaction between Recommendation source and Product type on Perceived transparency (b = .0004; p = .04). Participants perceived the Super Expert as more transparent for the Experience products ($M_{Super\ expert}$ = 5.54, SD = 0.83 vs. M_{AI} = 4.75, SD = 0.81, b = .787, p < .001). We found no significant difference in Perceived transparency between the two Recommendation sources for the Search product ($M_{Super\ expert}$ = 5.23, SD = 0.12 vs. M_{AI} = 4.91, SD = 0.12, b = .318, p = .076; Fig. 5 and Fig. 6).

To assess the overall indirect effect of Recommendation source and Product type on Intention to follow the recommendation through Perceived transparency and Perceived credibility, we conducted a regression analysis via PROCESS (Model 83—[118]). The analysis revealed a significant effect of Recommendation source on Perceived transparency (b = -.0079, p < .001) and a significant effect of Perceived transparency on Perceived credibility (b = .7116, p < .001), which significantly affected Intention to follow the recommendation (b = .3804, p < .001).

We also found a significant index of moderated mediation through Perceived transparency and Perceived credibility (b = .0013; LCI = .0001; UCI = .0028). Results showed that the indirect effect of Recommendation source on Intention to follow the recommendation based on Perceived transparency and Perceived credibility was not significant for the Search product (b = -.0009; LCI = -.0021; UCI = .0001), while it was significant for the Experience products (b = -.0021; LCI = -.0036; UCI = -.0009), Perceived transparency and Perceived credibility sequentially mediated the effect of Recommendation sources on Intention to follow the recommendation. Figure 7 summarizes these results.

5.3 Discussion

Study 2 replicated and extended the findings of Study 1, further supporting our proposed sequential mediation model and confirming H2. The results demonstrate that the effectiveness of the recommendation source depends not only on product type but also on the level of human expertise. When participants received advice from a highly experienced and reputed human recommender (vs. AI), they responded more favorably in the context of experience products, while no significant difference emerged for search products.

These findings highlight the critical role of human expertise in shaping perceptions of transparency, credibility, and intention to follow recommendations – especially for experience goods. Compared to a standard human recommender, the presence of a super expert significantly shifted consumer evaluations, underscoring how expertise can alter the perceived value of human input relative to AI. Taken together with the results of Study 1, these findings suggest a nuanced picture: AI tends to be more effective for search products, while highly qualified human recommenders are more persuasive for experience products. However, this raises the question of whether inte-

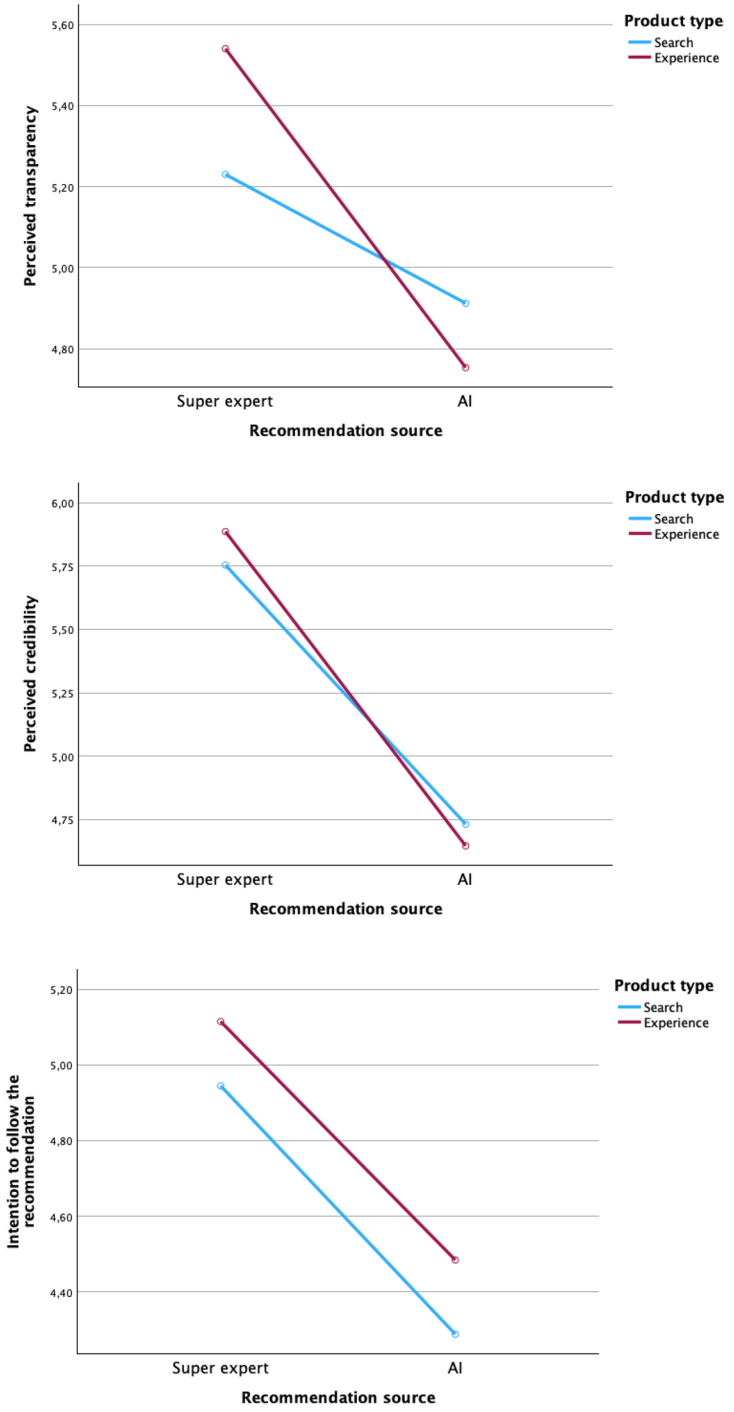


Fig. 5 Study 2: Interaction between Recommendation Source (AI vs. Super expert) and Product type (Search vs. Experience) on Perceived transparency, Perceived credibility, Intention to follow the recommendation

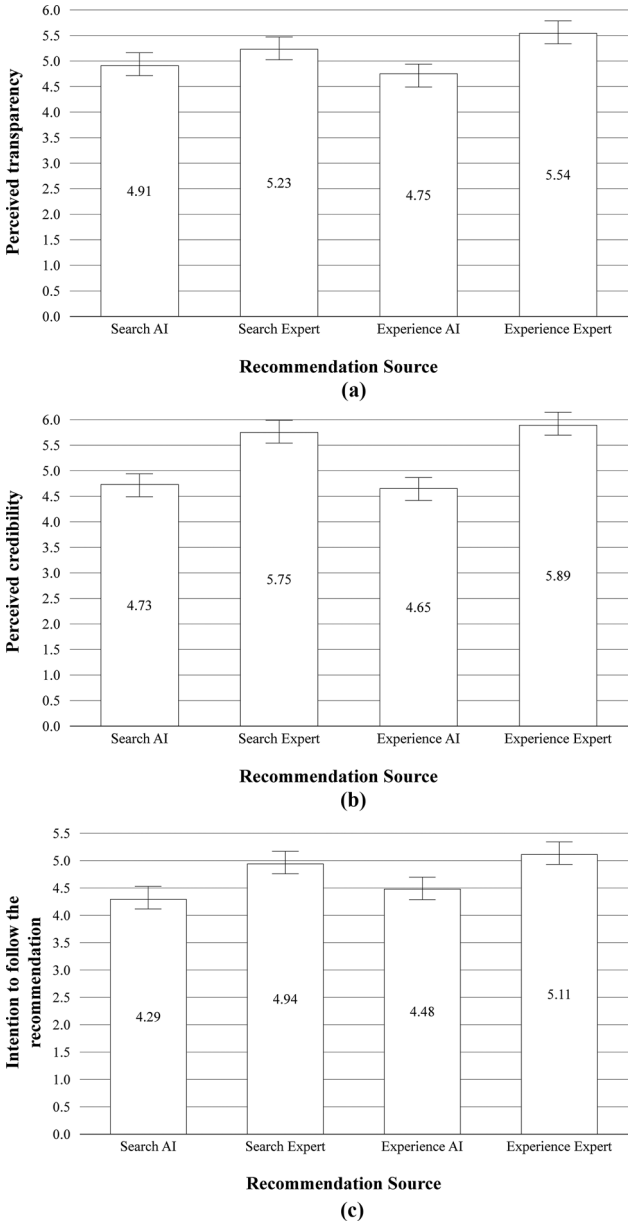


Fig. 6 Study 2: Bar Graphs with Standard Errors Bars (95% C.I.) by Perceived transparency, Perceived credibility, Intention to follow the recommendation

grating a super expert with AI into a hybrid recommendation source might enhance consumer responses across both product types. Study 3 addresses this question by comparing AI, super expert, and a combined human-AI hybrid source, exploring whether integration leads to enhanced consumer responses or introduces complexity that undermines trust.

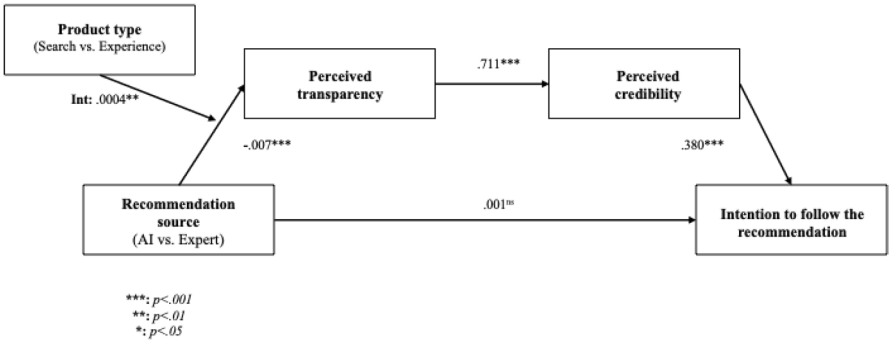


Fig. 7 Study 2: Results

6 Study 3

6.1 Method

A total of two hundred ninety-three participants (M_{Age} = 33.54 years, SD = 11.82, 42.7% male) were recruited via Prolific to take part in a between-subjects study in exchange for monetary compensation. All participants successfully passed the attention check and showed clear comprehension and recall of the stimulus they encountered. The study employed a design consistent with Study 2, but introduced three experimental conditions: Super expert, AI, and Super expert combined with AI. As in Study 2, the manipulation was constructed following the Cochran-Weiss-Shanteau approach [120].

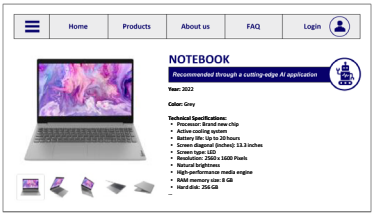
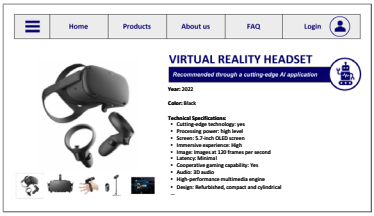
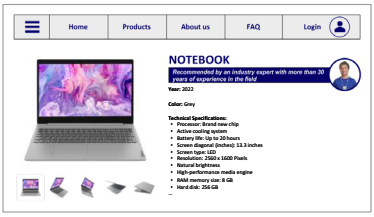
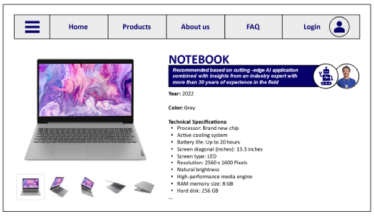
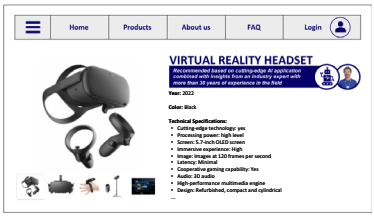
The Super expert condition employed the same stimuli used in Study 2, while the AI condition relied on the stimuli previously presented in Studies 1 and 2. In the Super expert combined with AI condition, the product recommendation was described as being generated by AI technology enriched with the expertise of an industry professional with over 30 years of experience.

Participants were randomly assigned to one of the three conditions: Super expert (N_{Search} = 47; $N_{Experience}$ = 50), AI (N_{Search} = 41; $N_{Experience}$ = 35), or Super expert combined with AI (N_{Search} = 57; $N_{Experience}$ = 63) (see Table 5). They were then asked to respond to the same set of questions administered in Studies 1 and 2 (see Web Appendix – Tables 8 and 9 for the measures of reliability and validity).

6.2 Results

The ANOVAs revealed no significant effects of Recommendation source when comparing AI alone to the Super expert combined with AI across all evaluated dimensions. Perceived transparency was similar between the two sources (M_{AI} = 5.87, SD = 0.95 vs. $M_{Super\ expert\ combined\ with\ AI}$ = 5.66, SD = 1.16, F(1, 194) = 1.713, p = .192), as was Perceived credibility (MAI = 5.68, SD = 1.17 vs. $M_{Super\ expert\ combined\ with\ AI}$ = 5.56, SD = 1.23, F(1, 194) = 0.467, p = .495). Intention to follow the recommendation was marginally higher for AI alone compared to the combined source (M_{AI} = 5.64, SD = 1.33 vs. $M_{Super\ expert\ combined\ with\ AI}$ = 5.24, SD = 1.55, F(1, 194) = 3.470, p = .064).

Table 5 Study 3: Stimuli and experimental conditions

	Search product	Experience product
AI condition		
Super expert condition		
Super expert combined with AI condition		

Description of Super expert combined with AI condition:"The expert has more than 30 years of experience in the field. He has obtained official certifications in the specific field and has acquired a solid education through practical experiences and individual studies during his more than 30-year career. Currently, he is recognized as an authority in the field by other experts and has received numerous awards and recognition for his influence in the field. He is reliable, timely and delivers accurate and informed recommendations. His insights are associated with cutting-edge AI recommendation systems, helping users receive more accurate, personalized, and effective guidance."

Similarly, no significant differences emerged between the Super expert alone and the Super expert combined with AI. Perceived transparency ratings were nearly identical ($M_{Super\ expert}=5.76$, $SD=1.08$ vs. $M_{Super\ expert\ combined\ with\ AI}=5.66$, $SD=1.16$, $F(1, 215)=0.424$, $p=.516$), and while Perceived credibility appeared marginally higher for the Super Expert alone ($M_{Super\ expert}=5.85$, $SD=0.98$ vs. $M_{Super\ expert\ combined\ with\ AI}=5.56$, $SD=1.23$, $F(1, 215)=3.449$, $p=.065$). Intention to follow the recommendation did not differ significantly between the two conditions ($M_{Super\ expert}=5.19$, $SD=1.46$ vs. $M_{Super\ expert\ combined\ with\ AI}=5.24$, $SD=1.55$, $F(1, 215)=0.058$, $p=.809$).

To further examine such effects, we proceeded by analyzing the data separately for each Product type. For Search products, the ANOVAs revealed significant effects of Recommendation source. The Super Expert was perceived as more transparent ($M_{Super\ expert}=5.90$, $SD=0.92$ vs. $M_{Super\ expert\ combined\ with\ AI}=5.44$, $SD=1.24$, $F(1, 102)=4.417$, $p=.038$) and more credible ($M_{Super\ expert}=5.91$, $SD=0.85$ vs. $M_{Super\ expert\ combined\ with\ AI}=5.46$, $SD=1.13$, $F(1, 102)=5.120$, $p=.026$) than the Super Expert combined with AI. However, Intention to follow the recommenda-

tion did not differ significantly between the two ($M_{Super\ expert}=5.35$, $SD=1.32$ vs. $M_{Super\ expert\ combined\ with\ AI}=4.93$, $SD=1.62$, $F(1, 102)=2.023$, $p=.158$). When comparing AI alone to the Super expert combined with AI, participants reported a significantly greater Intention to follow the recommendation when the source was AI ($M_{AI}=5.90$, $SD=1.36$ vs. $M_{Super\ expert\ combined\ with\ AI}=4.93$, $SD=1.62$, $F(1, 96)=9.814$, $p=.002$), while the Perceived credibility difference was marginally significant ($M_{AI}=5.87$, $SD=1.18$ vs. $M_{Super\ expert\ combined\ with\ AI}=5.46$, $SD=1.13$, $F(1, 96)=2.993$, $p=.087$). Thus, for Search products, adding AI to the Super expert appeared to diminish rather than enhance perceived recommendation quality.

In contrasts, the ANOVAs revealed no significant differences in Perceived transparency, Perceived credibility, or Intention to follow the recommendation when comparing the Super expert alone with the Super expert combined with AI for Experience products. Specifically, Perceived transparency did not differ between the two sources ($M_{Super\ expert}=5.64$, $SD=1.21$ vs. $M_{Super\ expert\ combined\ with\ AI}=5.87$, $SD=1.06$, $F(1, 111)=1.141$, $p=.288$), nor did Perceived credibility ($M_{Super\ expert}=5.79$, $SD=1.09$ vs. $M_{Super\ expert\ combined\ with\ AI}=5.66$, $SD=1.32$, $F(1, 111)=0.327$, $p=.568$). Likewise, participants showed no significant difference in their Intention to follow the recommendation ($M_{Super\ expert}=5.04$, $SD=1.59$ vs. $M_{Super\ expert\ combined\ with\ AI}=5.52$, $SD=1.44$, $F(1, 111)=2.801$, $p=.097$). Comparing AI alone to the Super expert combined with AI also yielded non-significant results across all variables, including Perceived transparency ($M_{AI}=5.70$, $SD=0.99$ vs. $M_{Super\ expert\ combined\ with\ AI}=5.87$, $SD=1.06$, $F(1, 96)=0.601$, $p=.440$), Perceived credibility ($M_{AI}=5.47$, $SD=1.13$ vs. $M_{Super\ expert\ combined\ with\ AI}=5.66$, $SD=1.32$, $F(1, 96)=0.498$, $p=.482$), and Intention to follow the recommandation ($M_{AI}=5.33$, $SD=1.25$ vs. $M_{Super\ expert\ combined\ with\ AI}=5.52$, $SD=1.44$, $F(1, 96)=0.407$, $p=.525$).

Subsequently, we conducted a series of regression analyses using PROCESS (Model 83—[118]) to examine how Product type (Search vs. Experience) moderates the impact of Recommendation sources on Perceived transparency, Perceived credibility, and ultimately, the Intention to follow the recommendation. Two scenarios were tested: one comparing a Super expert with a Super expert combined with AI, and another comparing AI with Super expert combined with AI. In both cases, we assessed how Recommendation source and Product type jointly influenced Intention to follow the recommendation through Perceived transparency and Perceived credibility.

Comparing the human Super expert with the Super expert combined with AI, results showed that Recommendation source significantly affected Perceived transparency ($b=-0.1530$, $p<0.05$). Specifically, Perceived transparency was higher in the Super expert condition than in the Super expert combined with AI condition. Perceived transparency, in turn, positively influenced Perceived credibility ($b=0.7761$, $p<0.001$), which impacted the Intention to follow the recommendation ($b=0.307$, $p<0.01$). The moderated mediation index was significant ($b=0.0547$; $LCI=0.0067$; $UCI=0.1327$), revealing that the indirect effect of Recommendation source on Intention to follow the recommendation, through Perceived transparency and Perceived credibility, was significant for Search products ($b=-0.0365$; $LCI=-0.0920$; $UCI=-0.0034$) but not for Experience products ($b=0.0182$; $LCI=-0.0160$; $UCI=0.0623$).

Similarly, when comparing AI with the Super expert combined with AI, Recommendation source significantly influenced Perceived transparency (b = -0.2913, $p < 0.01$) indicating that Perceived transparency was higher in the AI only condition. In turn, the Perceived transparency enhanced Perceived credibility (b = 0.796, $p < 0.001$) which then impacted the Intention to follow the recommendation (b = 0.2848, $p < 0.001$). The index of moderated mediation was also significant (b = 0.0854; LCI = 0.0150; UCI = 0.2070), showing that the indirect effect was significant for Search products (b = -0.0661; LCI = -0.1539; UCI = -0.0165) but not for Experience products (b = 0.0192; LCI = -0.0288; UCI = 0.0829) (see Fig. 8 and 9).

6.3 Discussion

Therefore, Study 3's findings supported H3, confirming that for search products the combination of AI and human expertise generally resulted in lower perceived transparency compared to either AI or the human super expert only, subsequently diminishing credibility and intention to follow recommendations. In other words, we found that while combining AI with human expertise can compete, in terms of transparency, credibility and intention to follow the recommendation for experience products, with AI or human expert only, it can have unintended negative effects for search products.

7 General discussion

7.1 Discussion of findings

The present research shows that consumers' intention to follow product recommendations from either AI or a human expert crucially depends on product type and on the level of perceived expertise of human recommenders. This relationship is mediated sequentially by consumers' perceptions of the source's transparency and credibility. Notably, while human recommenders were generally viewed as more credible at a surface level, participants nonetheless reported a stronger intention to follow recommendations from AI. This seeming contradiction is clarified by the fact that AI sources were seen as more transparent, and transparency – positioned earlier in our proposed mediation model – plays a foundational role in shaping subsequent credibility judgments.

Our findings reveal that, for search products, AI-generated recommendations are perceived as more transparent and credible than those provided by human agents, resulting in a higher intention to follow the recommendation. This advantage, however, does not extend to experience products, for which no significant differences emerged between sources. The superior performance of AI in the context of search products aligns with prior research comparing product categories that are more objective in nature – such as search, utilitarian, or functional products – against more subjective categories, such as experience, hedonic, or symbolic products [6, 8, 19–23, 72]. This may be explained by AI's superior analytical capabilities, which allow it to provide accurate and detailed information about product attributes – an aspect that is particularly valuable when evaluating search products [7, 98, 99]. While AI systems

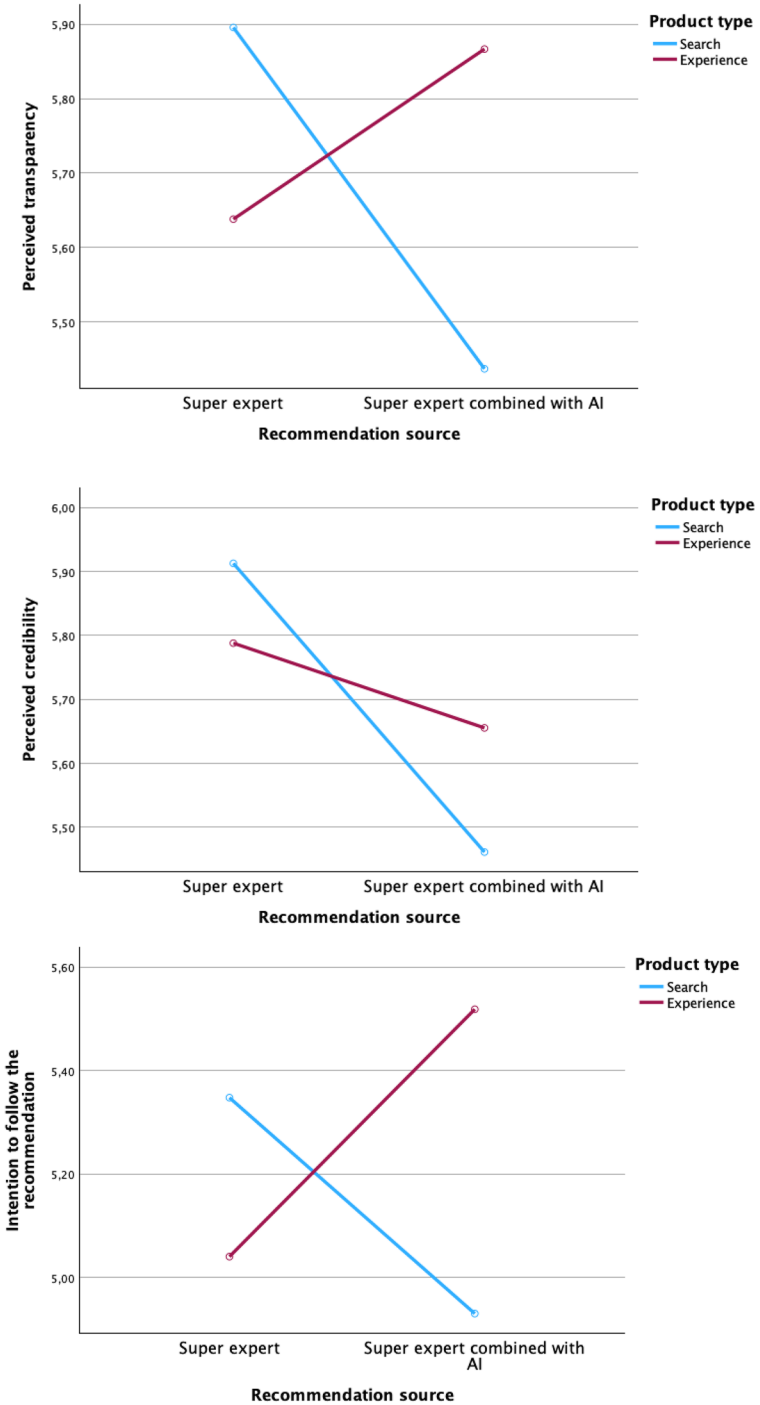
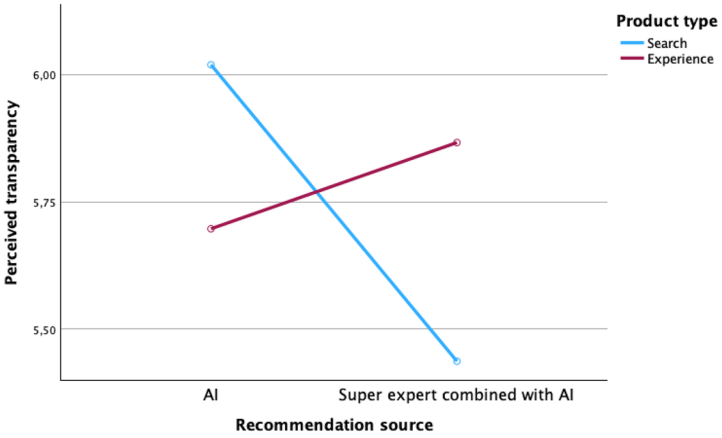
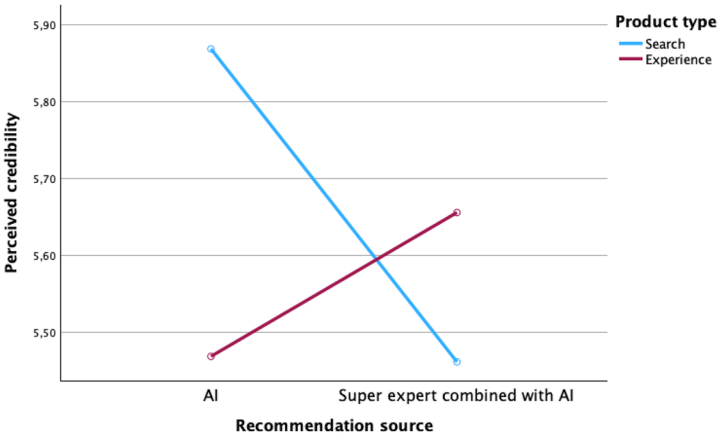


Fig. 8 Study 3: Interaction between Recommendation Source (AI vs. Super expert combined with AI and Super expert vs. Super expert combined with AI) and Product type (Search vs. Experience) on Perceived transparency, Perceived credibility, Intention to follow the recommendation





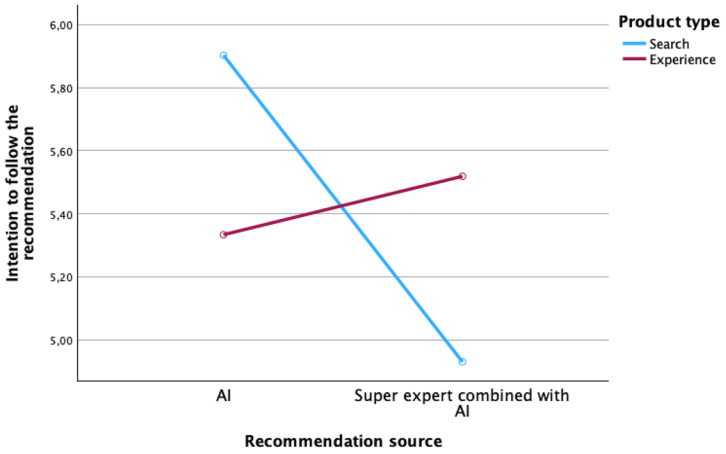
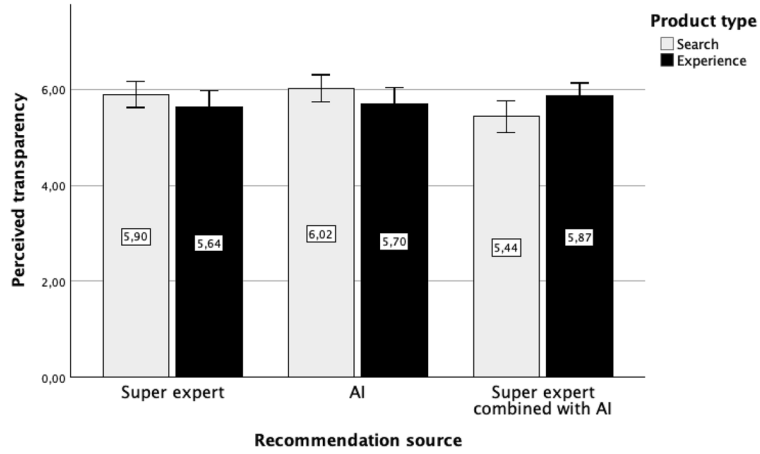
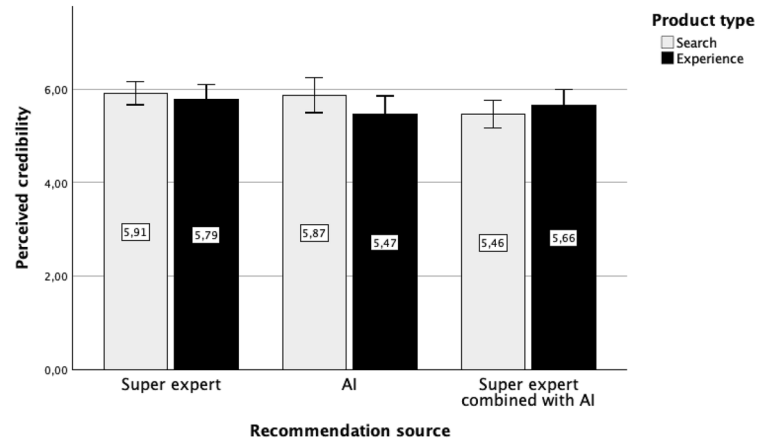


Fig. 8 (continued)





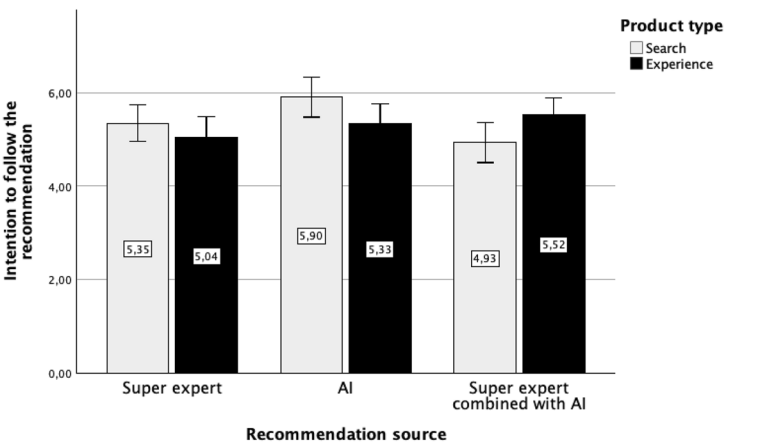


Fig. 9 Study 3: Bar Graphs with Standard Errors Bars (95% C.I.) by Perceived transparency, Perceived credibility, Intention to follow the recommendation

are often criticized for their opaque "black-box" nature [29, 75–77], this concern may be less salient for search products, where the objective nature of the information allows consumers to more easily infer the logic behind the AI's recommendation. As a result, AI may be perceived as particularly transparent in this context – supporting insights from previous studies on algorithmic transparency [29, 59, 81]. In contrast, for experience products – which typically require trial or personal experience to form a reliable judgment [23, 24, 102] – AI may be seen as less capable of accounting for the subjective and contextual nuances involved [107]. Consequently, consumers may struggle to understand how the AI system formulates its recommendation, leading to lower perceived transparency.

These insights support our initial assumptions but also prompt an important follow-up question: what happens when the human recommender is not generic but presented as a highly expert source? There is strong theoretical grounding for the idea that perceived expertise enhances transparency. Consumers may intuitively believe that a highly knowledgeable human – due to experience, interpretive skills, and context sensitivity – is better equipped to explain recommendations in a clear and relatable way [105, 106]. Consistent with research on source expertise and persuasion [86, 87, 108], our results indicate that when a human recommender is described as "highly expert, reputed, and qualified," the advantage of AI for search products disappears. In this scenario, the "Super Expert" human is equally likely to be trusted and followed as the AI. Furthermore, for experience products – where no significant difference was observed between a standard human and AI – introducing a Super Expert significantly increases consumers' intention to follow the recommendation. These findings underscore the central role of expertise in enhancing perceptions of transparency and credibility, particularly in contexts where subjective evaluation is paramount.

Building on this, we explored whether combining a Super Expert and AI into a hybrid recommendation source could further enhance consumer responses across both product types. While some literature suggests that human and AI agents may complement each other [6, 91], and hybrid sources can benefit from the strengths of both [49], our results show that this effect is context-dependent – echoing findings by Yang et al. [9] and Jin and Zhang [72]. Specifically, for search products, the hybrid source is evaluated less favorably than either AI or the Super Expert alone, while no significant advantage was found for experience products. A likely explanation lies in perceived role ambiguity. When the individual contributions of the human and AI agents are not clearly communicated, consumers may experience uncertainty about the source of the recommendation [93, 96], which undermines perceived transparency. For search products – where consumers seek objective, fact-based recommendations – AI alone may already be perceived as sufficient. Adding a human element could therefore be seen as redundant or even disruptive. In contrast, for experience products, where subjectivity and personalization matter more, the human expert helps contextualize the recommendation, enhancing transparency and bringing the hybrid source's effectiveness on par with the strongest single agents.

This holds significant relevance from both academic and managerial standpoints.

7.2 Theoretical implications

Our research makes several theoretical contributions. First, we extend the literature on the comparison between AI and human recommendation sources by empirically testing a sequential mediation model in which the recommendation source (human agent vs. AI vs. a combination of both) influences perceived transparency, which in turn affects perceived credibility and ultimately consumers' intention to follow the recommendation. Previous studies have shown that while consumers are increasingly open to interacting with algorithms, they often hesitate to adopt AI-generated recommendations [15, 16, 57, 59–61], likely due to a perceived lack of transparency that leads to uncertainty and distrust [3, 75, 78]. Although several studies have begun to explore the effects of transparency (e.g., [55, 77, 81]), the specific mechanisms through which transparency promotes the adoption of algorithmic versus human recommendations remain underexplored. We address this gap by proposing that perceived transparency influences consumers' behavioral intentions through its effect on perceived credibility – defined as the extent to which a recommender is regarded as competent and trustworthy [43]. Recent research supports this pathway. For instance, Ning et al. [29] showed that algorithmic transparency affects trust via beliefs about competence, integrity, and benevolence. Other studies [39, 40] have found that transparency positively influences credibility, although these relationships have been examined in different contexts and not explicitly in AI vs. human recommendation scenarios. Our findings address this gap by demonstrating that recommendation source influences perceived transparency, which in turn shapes perceived credibility and behavioral intention. We also investigate how this mechanism varies depending on product type (search vs. experience), offering insights into when and why different recommendation sources are more effective. In doing so, we extend the literature on the interaction between recommendation source (AI vs. human) and product type (e.g., [19, 23]), as well as related research examining similar categorical distinctions (e.g., [22, 72]). This sheds light on a novel psychological mechanism explaining consumer responses to human vs. AI-based recommendations.

Second, we incorporate the perceived expertise of the human recommender into our analysis. While prior research has consistently shown that expertise enhances the persuasiveness of human recommenders [43, 45, 86], its role in shaping consumer preferences between AI and human recommendation sources has not been fully examined. Recent findings suggest that algorithm aversion increases when the human alternative is framed as highly competent and decreases when human expertise is vague or low [18, 90]. We build on this literature by explicitly manipulating the level of expertise attributed to the human recommender. Our results show that a highly expert, reputable human agent performs on par with AI when recommending search products, and outperforms AI in the context of experience products. This contributes new insight into when human input is preferred over AI – and vice versa – based on the nature of the product and the expertise attributed to the human source.

Third, we enhance the completeness of our comparative framework by including hybrid recommendation sources-case where both AI and a human agent jointly deliver the recommendation. Although prior research suggests that human-AI hybrid systems can leverage complementary strengths and improve consumer responses

compared to AI-only or human-only sources [6, 9, 49], the effectiveness of hybrid versus single-source recommendations warrants further investigation. While hybrid sources may enhance perceived objectivity and reduce AI-related skepticism [49, 92], they may also introduce ambiguity about the roles played by each agent, potentially diminishing transparency and trust. Our findings reveal that when a hybrid source combines a highly expert human and an AI, it is actually less effective than either source alone in the context of search products, and yields no significant advantage for experience products. This suggests that in fact-based, rational decision contexts, multiple sources may create cognitive overload or conflicting information, reducing clarity rather than enhancing it. These results help clarify the conditions under which hybrid systems succeed and when they risk backfiring.

7.3 Practical implications

Our results provide relevant practical implications for companies as to how they should manage touchpoints to interact with customers along the decision-journey in the active evaluation phase, when customers rely on recommendations to develop informed judgments. For example, our findings can help retailers interested in deciding whether to employ AI or human agents in a broad offering which includes a mix of search and experience products.

Briefly, our experimental findings suggest companies to prefer AI-based recommendations when marketing search products, while they should prefer highly qualified human recommenders when marketing experience products. These results thus have clear implications also for touchpoint management: investing in highly skilled human advisors clearly pays off only when they should recommend experience products.

One of the most important managerial contributions is related to the understanding of hybrid approaches. Notably, as managers increasingly recognize that consumers engage in complex and diversified decision journeys [121] and interact with a variety of touchpoints [122], they often respond to this complexity by attempting to "over-delight" customers in their decision-making. Driven by their concern to exceed customer expectations and boost satisfaction indicators, managers tend to over-deliver, offering additional services or features beyond what is necessary or beneficial to customers [123]. Our results suggest that such an overemphasis on delighting customers may prove counterproductive, yielding minimal tangible value relative to the associated costs.

In practice, this may lead managers to build overly complex and redundant recommendation systems by combining expert input with AI. However, our empirical observations suggest that such hybrid configurations (human expert and AI), often fail to yield substantive improvements in customer outcomes. Consequently, operational costs escalate without delivering proportional benefits, thus underscoring a core managerial dilemma. Rather than reassessing this trajectory, organizations frequently respond by compounding complexity: introducing AI-enhanced recommendations from so-called Super Experts. These solutions, while even more resource-intensive, do not necessarily translate into improved performance and are significantly more difficult to scale. The present research clarifies a paradoxical dynamic: managers

seeking to avoid underperformance in customer outcomes by over-delighting them – through recommendations driven by a hybrid combination of expert input and artificial intelligence (AI) – tend to exacerbate, rather than resolve, performance issues. This pattern might lead to both increased costs (i.e., use of more recommendation agents) and a decline in customers willingness to follow the recommendation.

We explore the mediating mechanisms underlying this phenomenon and demonstrate that increased system sophistication does not inherently lead to higher perceived transparency, credibility and intention to follow the recommendation.

Our study also shed light on the importance of adopting transparency as a corporate value for companies that decide to share information through recommenders, whether human or AI-based. In the presence of transparency, advisors are perceived as credible when they share such information and succeed in guiding consumer behavior. Companies that consciously and proactively decide to be transparent are rewarded by consumers, as well as all other stakeholders, for their perceived ethical conduct. Indeed, such transparency translates into a perception of the company's openness to be subject to verification of the source and reliability of its information.

7.4 Limitations and future research

While offering interesting contributions to research and practice, our study features limitations that can represent fruitful avenues for future work. For instance, scholars could investigate factors different than the level of human recommenders' expertise to change consumers' perceptions about AI's vis-à-vis human agents' transparency and credibility. For instance, one could examine the role of consumers' expertise about the product in driving their reactions. Moreover, while we investigated search versus experience products, other scholars could study other product-related moderators or situational factors, such as the possibility to try the product before buying it. One could think that human agents could be perceived as particularly effective in driving product purchases (compared to AI) when consumers have the possibility to try the product. Another limitation of our study is that we did not control for individual differences related to AI avoidance or resistance. Prior research has shown that consumers' attitudes toward AI can significantly shape their responses to AI-generated recommendations, that may influence how participants evaluated the different recommendation sources, particularly in the AI and hybrid conditions. Future studies could benefit from including validated measures of AI resistance or algorithm aversion to better account for these individual differences. Future work could also examine additional characteristics of human recommenders, such as the level and depth of relationship with the advisee (e.g., friends or family members), either in isolation or combined with the perceived level of expertise, and their perceived performance compared to AI recommenders. Other limitations are related to the fact that the hybrid recommendation condition, described as a combination of super expert and AI, may also lack clarity for participants regarding how the two sources interact. Without explicit transparency about the respective contributions of the AI and the human, participants may have defaulted to assumptions, potentially biasing results. In addition, the credibility of the "super expert" profile was established through experimental manipulation, but in real-world, consumers may have different thresholds or defini-

tions of what constitutes high expertise, influenced by prior experience or knowledge of the topic. Moreover, our experimental manipulations presented static, one-shot recommendations, while in real-world contexts, consumers often interact with recommendation agents repeatedly, and their evaluations may evolve over time through learning, feedback, or changes in perceived personalization.

Overall, given the relevance of the topic for both marketing research and practice, we believe more empirical evidence about situational, psychological, and individual factors affecting consumer preference for AI versus human recommenders would be important.

Appendix

See Tables, 6, 7, 8, 9

Table 6 Measurement items

Scales
Perceived transparency [112, 113]
1. I believe the recommendation source follows transparent work processes while recommending the product
2. I believe the recommendation source will provide me with in-depth access to the product information while recommending the product
3. I believe the recommendation source will provide me with in-depth knowledge about the product information while recommending the product
4. I believe the recommendation source will provide me with transparent product information while recommending the product
5. I believe the recommendation source will provide me with comprehensive product information while recommending the product
Perceived credibility [43]
1. Dependable/Undependable
2. Honest/Dishonest
3. Reliable/Unreliable
4. Sincere/Insincere
5. Trustworthy/Untrustworthy
6. Expert/Not an expert
7. Experienced/Inexperienced
8. Knowledgeable/Unknowledgeable
9. Qualified/Unqualified
10. Skilled/Unskilled
Intention to follow the recommendation [14]
1. Seeing such results, I would follow this recommendation

Table 7 Results of the pretested products

Search	Freq	Experience	Freq
Notebook	46	Virtual reality games	57
Speaker Bluetooth	46	Digital camera	39
Smartwatch	45	Videogames	39
Phone	44		
Alarm system	34		

Table 8 Model assessment – convergent validity for Study 1,2 and 3

Construct(s)	Item(s)	Study 1								Study 2								Study 3							
		M	SD	CFA loading	SMC	t value	*p*	α	AVE	M	SD	CFA loading	SMC	t value	*p*	α	AVE	M	SD	CFA loading	SMC	t value	*p*	α	AVE
Perceived transparency	1. I believe the recommendation source follows transparent work processes while recommending the product.	4.550	1.310	0.780	0.576	11.114	***	0.934	0.680	4.550	1.320	0.690	0.480	11.800	***	0.88	0.684	5.500	1.430	0.850	0.730	18.890	***	0.939	0.756
	2. I believe the recommendation source will provide me with in-depth access to the product information while recommending the product.	5.290	1.000	0.833	0.648	11.222	***			5.300	1.000	0.810	0.650	14.640	***			5.770	1.260	0.880	0.770	19.770	***	0.939	
	3. I believe the recommendation source will provide me with in-depth knowledge about the product information while recommending the product.	5.390	1.070	0.839	0.662	11.317	***			5.390	1.070	0.810	0.660	14.870	***			5.810	1.270	0.890	0.790	20.270	***	0.939	
	4. I believe the recommendation source will provide me with transparent product information while recommending the product.	4.930	1.230	0.826	0.558	10.516	***			4.940	1.240	0.750	0.560	13.150	***			5.590	1.310	0.870	0.760	19.510	***	0.939	
	5. I believe the recommendation source will provide me with comprehensive product information while recommending the product.	5.410	1.010	0.843	0.656	11.228	***			5.410	1.010	0.810	0.660	14.780	***			5.810	1.230	0.870	0.750	19.380	***	0.939	
Perceived credibility	1. Dependable/Undependable	5.093	1.170	0.799	0.544	12.599	***	0.942	0.661	5.090	1.170	0.740	0.540	13.340	***	0.94	0.635	5.510	1.490	0.840	0.700	18.530	***	0.953	0.670
	2. Honest/Dishonest	4.900	1.150	0.738	0.543	10.519	***			4.910	1.150	0.670	0.440	11.610	***			5.450	1.530	0.790	0.620	16.830	***	0.953	
	3. Reliable/Unreliable	5.220	1.210	0.830	0.589	12.275	***			5.220	1.210	0.770	0.590	14.110	***			5.600	1.390	0.860	0.740	19.310	***	0.953	
	4. Sincere/Insincere	4.550	1.430	0.819	0.608	12.492	***			4.550	1.430	0.780	0.610	14.440	***			5.370	1.520	0.800	0.630	17.120	***	0.953	
	5. Trustworthy/Untrustworthy	4.930	1.200	0.808	0.546	11.779	***			4.940	1.210	0.740	0.550	13.370	***			5.500	1.480	0.800	0.640	17.180	***	0.953	
	6. Expert/Not an expert	5.530	1.410	0.876	0.651	14.450	***			5.530	1.410	0.890	0.790	17.740	***			5.740	1.360	0.800	0.640	17.330	***	0.953	
	7. Experienced/Inexperienced	5.440	1.480	0.847	0.641	13.935	***			5.450	1.490	0.860	0.740	16.810	***			5.800	1.400	0.840	0.700	18.510	***	0.953	
	8. Knowledgeable/Unknowledgeable	5.550	1.380	0.807	0.569	13.169	***			5.560	1.390	0.820	0.670	15.520	***			5.830	1.360	0.810	0.660	17.580	***	0.953	
	9. Qualified/Unqualified	5.840	1.180	0.783	0.606	12.465	***			5.850	1.190	0.780	0.610	14.400	***			5.970	1.240	0.820	0.670	17.930	***	0.953	
	10. Skilled/Unskilled	5.500	1.300	0.818	0.649	13.165	***			5.510	1.300	0.820	0.670	15.510	***			5.820	1.320	0.840	0.710	18.660	***	0.953	

Table 9 Discriminant validity – Comparison of Average Variance Extracted (AVE) and correlations

	Study 1		Study 2		Study 3	
Item	*Perceived credibility*	*Perceved transparency*	*Perceived credibility*	*Perceived transparency*	*Perceived credibility*	*Perceved transparency*
Perceived credibility	0.661		0.635		0.670	
Perceved transparency	0.634	0.680	0.610	0.684	0.634	0.756
Intention to follow the recommendation	0.446	0.521	0.620	0.670	0.446	0.521

Funding Open access funding provided by Luiss University within the CRUI-CARE Agreement. No funding has been granted to this study.

Declarations

Conflict of interest Authors declare no conflict of interest.

Ethical approval The work has been revised and approved by the Luiss University Ethical Committee.

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