Professional Design, User Design, or AI Design? The Psychological Mechanism of the Design Source Effect

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Abstract

Design source effect refers to the influence of information regarding the source of a firm' s product design on consumers' product preferences and attitudes toward the firm. Currently, professional designers, users, and AI represent three common sources of product design. These three design sources exert positive or negative influences on consumer psychology and behavior through distinct mechanisms of action. Specifically, competence constitutes the mechanism underlying the professional design source effect; competence, power, and psychological distance serve as the mechanisms underlying the user design source effect; while value and information represent the mechanisms underlying the AI design source effect. Furthermore, the design source effect is subject to boundary conditions, being constrained by consumer, product, and firm factors. Future research may deeply investigate consumers' responses to hybrid design sources and further explore the mechanisms and boundary conditions of the design source effect.

Full Text

Preamble

Professional Design, User Design, or AI Design? The Psychological Mechanisms of the Source of Design Effect

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Abstract: The source of design effect refers to how information about a firm' s product design source influences consumer product preferences and corporate attitudes. Currently, professional designers, users, and AI represent three common sources of product design. These three design sources exert positive or negative influences on consumer psychology and behavior through distinct mechanisms. Specifically, competence constitutes the mechanism underlying the professional design source effect; competence, power, and psychological distance serve as the mechanisms underlying the user design source effect; while value and information represent the mechanisms underlying the AI design source effect. Moreover, the source of design effect operates under boundary conditions constrained by consumer, product, and firm factors. Future research should deeply explore consumer reactions to mixed design sources and further investigate the mechanisms and boundary conditions of the source of design effect.

Keywords: source of design effect, product design communication, professional design, user design, artificial intelligence design
Classification: B849; F713.55

1 Introduction

Product design constitutes a critical source of competitive advantage for firms (Jindal et al., 2016). Beyond the design itself, effectively communicating product design to consumers proves equally vital to business success (Sample et al., 2024). Information about "who designed the product" has garnered increasing attention as part of product design communication (Fuchs et al., 2013; Song et al., 2021; Xu & Mehta, 2022; Zhang et al., 2022). Currently, besides professional designers, both users and AI have begun playing the role of product creators in corporate value creation (Schreier et al., 2012; Zhang et al., 2022). For instance, users participate in new product design by expressing needs or sharing design solutions on open innovation platforms such as Xiaomi Community, Midea Maker, and Haier HOPE. Lantu Automobile embraces the philosophy of user co-creation, encouraging deep user involvement in automotive R&D processes. Brands like Snow Beer and Yili have launched product packaging designed by AI to attract consumers. Xiaomi' s official account on Xiaohongshu hosted a design competition for Mi Band 8 wristbands, supporting users in designing with AI assistance. Simultaneously, some firms actively promote their design sources. Hermès, Louis Vuitton, IKEA, and numerous other brands emphasize in product promotions that items were designed by renowned designers. Threadless prints user designers' names on T-shirt labels. LEGO stamps "Designed by LEGO fans"on product packaging. Zhong Xue Gao actively publicized at product launches that the name, packaging, and flavor of its new "Sa' Saa" product were all AI-designed. When promoting new products, firms attempt to leverage product design source as a marketing selling point, raising important questions about how consumers react to different design sources and whether firms should advertise their design source information.

Existing product design research primarily focuses on design dimensions (Homburg et al., 2015; Jindal et al., 2016; Mishra, 2016) and how specific design dimensions affect consumer preferences (Caprioli et al., 2023; Heitmann et al., 2020; Liu et al., 2017; Simonov et al., 2023). Research on how design source information influences consumer preferences or corporate attitudes remains in its infancy. Previous studies on the source of design effect have mainly compared consumer reactions to user versus professional design (王海忠 & 闫怡, 2018; Dahl et al., 2015; Fuchs et al., 2013; Liljedal, 2016), AI versus professional design (Xu & Mehta, 2022; Zhang et al., 2022), and identified conditions under which consumers prefer user design (宋晓兵 et al., 2017; Paharia & Swaminathan, 2019; Song et al., 2021) or AI design (Zhang et al., 2022).

However, previous research on the source of design effect remains fragmented in four key aspects. First, design source manipulations lack consistency, with some studies manipulating design source at the firm level (Dahl et al., 2015; Fuchs & Schreier, 2011; Zhang et al., 2022) and others at the product level (Fuchs et al., 2013; Nishikawa et al., 2017; Schreier et al., 2012). Second, comparison objects differ, with some comparing users to professional designers (王海忠 et al., 2017; Nishikawa et al., 2017; Schreier et al., 2012), others comparing AI to professional designers (Xu & Mehta, 2022; Zhang et al., 2022), and still others comparing AI to human designers (Granulo et al., 2021). Third, research on mechanisms and boundary conditions remains scattered. For example, various perspectives exist on why firms employing user design are more popular than those using professional design, with some finding that consumers perceive user-design firms as more customer-oriented (Fuchs & Schreier, 2011), others concluding these firms are seen as more innovative (Schreier et al., 2012), and still others suggesting consumers identify more strongly with them (Dahl et al., 2015). Fourth, studied products vary widely, encompassing both aesthetically-oriented items like fashion (Fuchs et al., 2013; Xu & Mehta, 2022), T-shirts (Dahl et al., 2015; Schreier et al., 2012; Zhang et al., 2022), and posters (Granulo et al., 2021), as well as functionally-oriented products like laptops (Liljedal, 2016), mobile phones (王海忠 et al., 2017; 王海忠 & 闫怡, 2018), and bicycles (Fuchs & Schreier, 2011).

Given this complexity, this paper focuses on the three common design sources — "professional designers," "users," and "AI" —to examine consumer psychological and behavioral reactions, underlying mechanisms, and boundary conditions. Synthesizing and reviewing literature on the source of design effect holds theoretical significance: it clarifies the concept, compares how the three design sources influence consumer psychology and behavior, categorizes their mechanisms and boundary conditions, identifies research gaps and inconsistencies, and points directions for future research. Additionally, this systematic review offers practical value by guiding firms on when to communicate product design source information to consumers.

2.1 The Concept of Source of Design Effect

New product development comprises two main stages: design and production. The former transforms perceived gaps in user experience into solutions, while the latter converts solutions into products. Design represents an information processing activity that addresses perceived gaps between users' current and desired states to formulate product solutions (Ulrich, 2011). Design originates from perceived gaps in user experience and involves conceiving and developing new product solutions through innovative problem-solving (Verganti et al., 2020). Design can be categorized by source, with current classifications including professional design, user design, and AI design. Since employing professional designers better facilitates management of innovation activities, competitive advantage formation, and strategic alignment, professional design remains the mainstream approach in practice (Poetz & Schreier, 2012). However, with internet technology development and proliferation, user design and AI design have become increasingly common (Haefner et al., 2021; Song et al., 2021).

Information about whether a product was designed by professional designers, users, or AI may influence consumer product evaluations or corporate attitudes. Product design source functions as a peripheral cue—a heuristic that simplifies decision-making. The source of design effect can occur at either the firm or product level. At the firm level, the effect manifests as changes in consumer attitudes and behaviors toward a firm described as using different new product design sources. At the product level, it represents the impact of different design source descriptions for the same product on consumer preferences. The source of design effect does not aim to identify which design approach actually produces more popular products, but rather explores psychological perception differences toward various design source information. Overall, the source of design effect refers to differential consumer reactions to a firm or product described as employing different design sources. Investigating this effect can guide firms on when to communicate product design source information to consumers.

2.2 Differences Among Professional Design, User Design, and AI Design

Professional design originates from experts in specific product category design fields. Design experts possess the skills and capabilities to complete most design tasks efficiently and with high quality (Ulrich, 2011). User design refers to firms relying on user communities to generate new product design ideas and launching these products to broader consumer markets (Dahl et al., 2015; Fuchs et al., 2013; Schreier et al., 2012), representing an innovation method that improves new product success rates (Liljedal, 2016). In professional design, users typically provide only need information while professional designers provide solutions. In contrast, user design involves users providing both need information and solutions (Allen et al., 2018; Bayus, 2013; Lilien et al., 2002). AI refers to any machine using algorithms or statistical models to perform human cognitive functions such as perception, cognition, and conversation (Longoni et al., 2019). AI comprises three elements: data collection and storage, statistical and computational techniques, and output systems (Puntoni et al., 2021).

Thus far, product design and development have remained human designers' strengths (Xu & Mehta, 2022), but AI' s emergence and development have gradually transformed human production methods. Through big data processing, machine learning, and deep learning technologies, AI has become an important source of product design (Zhang et al., 2022).

Product design quality depends on two aspects: the designer' s understanding of consumer needs and their ability to provide design solutions. The three design sources—professional designers, users, and AI—differ along these two dimensions. Regarding understanding consumer needs, users, as members of the same consumer group, hold advantages over professional designers, typically possessing more accurate and detailed consumer need models (Moreau & Herd, 2010; Randall et al., 2007). AI' s data processing and learning capabilities exceed those of users. With access to large volumes of consumer text data, AI can analyze this information to understand group needs and preferences and identify trends (Kakatkar et al., 2020; Libai et al., 2020; Verganti et al., 2020). Users' understanding of consumer needs relies more on individual or small-group experiences. Therefore, given access to substantial valid consumer text data, AI holds advantages over users in understanding group consumer needs. However, since AI lacks human-like perception abilities and emotions, it may overlook certain consumers' implicit needs and emotional appeals.

Regarding the ability to provide design solutions, professional designers possess higher domain expertise than users, giving them advantages in developing solutions (Moreau & Herd, 2010; Randall et al., 2007; Von Hippel, 1998). AI overcomes human limitations in information processing scale, scope, and capacity, rapidly generating numerous design solutions and improving design efficiency (Haefner et al., 2021; Verganti et al., 2020). Consequently, for products with low design complexity that require minimal expertise to develop solutions, users can leverage their deep understanding and insights into consumer needs to propose unique and valuable design solutions (Kristensson et al., 2004; Nishikawa et al., 2013; Poetz & Schreier, 2012). For highly complex products, professional designers and AI can utilize their strong solution-providing capabilities to propose more feasible design solutions (Kristensson et al., 2004; Poetz & Schreier, 2012; Verganti et al., 2020). When product design complexity reaches a certain threshold, AI' s advantages in processing complex information become more pronounced, potentially outperforming professional designers in product design.

2.3.1 Consumer Reactions to User Design

Compared to professional design, consumers exhibit both positive and negative reactions to user design, manifesting in product preferences and corporate attitudes, as summarized in Table 1 .

Table 1 Consumer Reactions to User Design

Reaction Category	Dimension	Findings	Source
Positive	Product Preference	Consumers show higher willingness to pay for user-designed products	Schreier et al., 2012
		Consumers show higher purchase intention for products from user-design firms or products labeled "user-designed"	Dahl et al., 2015; Nishikawa et al., 2017
		Products labeled "user-designed" demonstrate better market performance	Nishikawa et al., 2017
	Corporate Attitude	Consumers hold better attitudes toward user-design firms	Fuchs & Schreier, 2011
		Consumers show more positive behavioral intentions toward user-design firms	Fuchs & Schreier, 2011; Schreier et al., 2012
		Consumers demonstrate higher identification with user-design firms	Dahl et al., 2015

Reaction Category	Dimension	Findings	Source
		When brands utilize brand community users to design new products, brand community members develop stronger self-brand connections and brand attachment	王海忠 et al., 2017; 王海忠 & 闫怡, 2018
Negative	Product Preference	Consumers show lower purchase intention for user-designed luxury goods	Fuchs et al., 2013
	Corporate Attitude	Consumers hold poorer attitudes toward unfamiliar brands using user design for complex products	Liljedal, 2016

Source: Compiled from literature.

In the product preference dimension, positive reactions manifest as higher purchase intention, willingness to pay, and better market performance for user-designed products. Schreier et al. (2012) simultaneously manipulated design source at both product and firm levels to reveal differences in consumers' willingness to pay across design sources. In their experiment, after providing identical corporate background and product information to all participants, they randomly assigned participants to "user design" and "professional design" groups. The user design group learned that breakfast cereal was designed by users and that the firm's new products were all designed by its user community members. The professional design group learned that cereal was designed by the firm's professional designers and that all new products were designed by professionals. Participants' maximum willingness to pay for the cereal was then measured through an auction procedure, revealing higher willingness to pay for user-designed products. Dahl et al. (2015) manipulated design source at the firm level to identify differences in purchase intentions for products from firms using different design sources. Researchers randomly divided participants into two groups, informing one group that Firm A’ s products were user-designed while Firm B’ s were internally designer-designed, and vice versa for the other group. After presenting two different neutral T-shirts, one from each firm, participants indicated which they would prefer to purchase. Results showed consumers preferred products from user-design firms. Nishikawa et al. (2017) conducted two field experiments testing whether labeling products as “user-designed” improved market performance. In a 67-day study across 46 Muji stores in Japan, researchers randomly selected some stores to display “based on user ideas” labels on electronic safety buzzers while leaving other stores’ products unlabeled. Stores displaying user design labels sold more safety buzzers. A subsequent 16-day study across 194 Muji stores using pretzels with different experimental designs replicated these findings, showing better market performance for products with user design labels. Additionally, in one online and one lab experiment manipulating design source at the product level, Nishikawa et al. (2017) found consumers exhibited higher purchase intentions for products displaying user design compared to those without such display, and compared to those displaying corporate designer design, regardless of actual design source.

In the corporate attitude dimension, positive reactions manifest as better attitudes, more positive behavioral intentions, higher identification, and stronger self-brand connections and brand attachment among brand community members learning that new product ideas originated from community users. Fuchs and Schreier (2011) revealed design source effects on corporate attitudes through multi-category studies involving T-shirts, furniture, and bicycles. In the T-shirt study, all participants learned about four startup firms (A, B, C, D) employing different design approaches: Firm A used zero delegation (corporate development and selection), Firms B and C used partial delegation (users either developed or selected designs), and Firm D used complete delegation (users both developed and selected designs). After viewing matched product sets of equal attractiveness (pre-tested and randomly assigned), participants completed corporate attitude measures and chose among the four firms to measure behavioral intentions. Results showed partial and complete delegation strategies positively influenced corporate attitudes and behavioral intentions compared to zero delegation, with similar findings for furniture and bicycles. In two breakfast cereal experiments and one T-shirt experiment simultaneously manipulating design source at product and firm levels, Schreier et al. (2012) found consumers were more willing to purchase products from user-design firms, recommend such firms to others, and recommend their products. Dahl et al. (2015), manipulating design source at the firm level, found participants identified more strongly with user-design firms. Furthermore, 王海忠 et al. (2017) and 王海忠 and 闫怡 (2018) demonstrated through multiple experiments that informing mobile phone brand community members that next-generation product ideas originated from community users rather than internal developers increased members' self-brand connections and brand attachment.

In the product preference dimension, negative reactions manifest as lower purchase intentions for user-designed luxury goods. Fuchs et al. (2013) manipulated design source at the product level to test negative effects of user design for luxury goods. In one experiment, pre-tests identified three well-liked luxury brands that came to participants' minds first: Gucci, Hermès, and Armani. Another pre-test created two equally preferred fashion product series (Series A and B) for each brand. In the main experiment, participants were randomly assigned to conditions where either Series A was user-designed and Series B corporate-designed, or vice versa. After viewing both series for each brand (presented in random order), participants indicated from which series they would purchase if buying from that brand. Results showed that across all three luxury brands, describing a series as user-designed decreased its selection frequency.

In the corporate attitude dimension, negative reactions manifest as poorer attitudes toward unfamiliar brands using user design for complex products. Liljedal (2016) manipulated design source at the product level to examine consumer reactions to different design sources for complex products like Dell laptops and Nike running shoes. Participants were first randomly assigned to familiar or unfamiliar brand conditions (with brand information present or absent on product images), then randomly assigned via product advertisements to user design or internal designer design conditions. Brand attitudes were measured using 7-point scales. Results revealed that consumers held poorer attitudes toward unfamiliar brands using user design for complex products.

2.3.2 Consumer Reactions to AI Design

While numerous studies examine consumer preferences for AI, limited literature addresses reactions to AI as a design source, representing an emerging trend in AI-product design integration. Previous findings on consumer reactions to AI design remain inconsistent, with some studies indicating AI design increases willingness to pay while others show it decreases purchase intentions and luxury attitudes.

First, AI design can increase consumers' willingness to pay. Zhang et al. (2022) manipulated design source at the firm level to examine consumers' willingness to pay for products from AI-design firms. Selecting T-shirts as a common product, researchers randomly assigned participants to "AI design" and "professional design" groups. The AI design group learned that product concepts and designs were developed by AI designers, while the professional design group learned they were developed by professionally hired designers. After viewing identical T-shirt images, participants responded to the question "How much money would you be willing to spend on this T-shirt from the firm?" Results showed consumers exhibited higher willingness to pay for products from AI-design firms compared to professional-design firms.

Second, AI design can decrease consumers' purchase intentions. Granulo et al. (2021) manipulated design source at the product level to test consumers' purchase intentions for AI-designed versus human-designed products. Participants were randomly assigned to four conditions: high symbolic value with human design, high symbolic value with AI design, low symbolic value with human design, and low symbolic value with AI design. Participants imagined being a doctor needing a skull poster. In high symbolic value scenarios, the poster decorated an office; in low symbolic value scenarios, it educated patients. Participants viewed two adjacent skull posters, with right/left design attribution varying by condition (human vs. AI). Results showed consumers exhibited lower purchase intentions for AI-designed products across both symbolic value conditions, though this negative effect weakened under low symbolic value.

Third, AI design can diminish consumers' attitudes toward luxury goods. Xu and Mehta (2022) manipulated design source at the product level, finding that compared to professionally designed luxury goods, consumers held negative attitudes toward AI-designed luxury goods. They selected Louis Vuitton as a luxury brand and Gap as a non-luxury brand, randomly assigning participants to four conditions: Louis Vuitton using AI design, Louis Vuitton using professional design, Gap using AI design, and Gap using professional design. Participants learned that new fashion product series were designed by either AI or chief designers. Using 7-point scales to measure attitudes toward the upcoming fashion series, results showed AI design significantly reduced attitudes toward Louis Vuitton' s new products compared to professional design, but did not significantly affect attitudes toward Gap' s new products.

These studies reveal that for products with low design complexity, consumers consistently show more positive reactions to user design across firm-level, product-level, and combined manipulations. These positive reactions manifest either as more positive attitudes and behavioral intentions toward user-design firms, or as higher purchase intentions for products from user-design firms or those labeled "user-designed." For highly complex products, brand community members learning that new products were designed by community users strengthens their emotional attachment to the brand. However, this does not mean consumer reactions to user design are always positive; reactions are negative for user-designed luxury goods and unfamiliar brands using user design for complex products. Literature on consumer reactions to AI design shows inconsistent conclusions. Firm-level manipulations suggest higher willingness to pay for AI design compared to professional design, while product-level manipulations show lower purchase intentions for AI design compared to human design. Negative effects of AI design are particularly pronounced for high symbolic value products and luxury goods. These inconsistent reactions may stem from multiple factors, including product type (common T-shirts and mugs in positive-effect studies versus specialized skull posters in negative-effect studies) and decision nature (everyday consumer choices in positive-effect studies versus imagined professional purchases in negative-effect studies). Future research should examine whether consumption context professionalism or consumer expertise moderates reactions to AI design.

3.1 Psychological Mechanisms of Professional Design Effects

The psychological mechanism underlying positive consumer reactions to professional design can be summarized as a competence mechanism, wherein perceived product quality and corporate trust influence consumer preferences and attitudes toward professional design.

Professional designers signify professionalism and authority. Moreau and Herd (2010) note that "professionals typically hold significant advantages over consumers in knowledge, training, and experience, advantages that may be real or subjectively perceived." Professional design appeals more strongly to consumers with high power distance beliefs. These consumers expect and accept unequal power distribution, believing high-power individuals possess greater decision-making competence. Consequently, high power distance belief consumers show greater respect for professional designers' knowledge and authority, enhancing their corporate trust and perceived product quality, which further increases their preference for professional-design firm products (Paharia & Swaminathan, 2019; Song et al., 2021).

3.2 Psychological Mechanisms of User Design Effects

Consumer reactions to user design—both positive and negative—can be summarized through three mechanisms: competence, power, and psychological distance.

3.2.1 Competence Mechanism

From a competence perspective, perceived innovation capability, perceived customer orientation, and perceived product quality serve as specific psychological mechanisms. First, for firms producing low-complexity products, user design's characteristics—numerous users, belonging to the same consumer group, fewer constraints, and diversity—lead consumers to believe users can generate novel and useful ideas, enhancing perceptions of user-design firms' innovation capabilities and increasing purchase intentions, willingness to pay, and recommendation intentions for both functional and aesthetic products (Schreier et al., 2012). Second, consumers perceive user-design firms as placing customers in extremely important positions, better able to respond to and satisfy customer needs, thereby increasing perceived customer orientation and product preferences (Dahl et al., 2015; Fuchs & Schreier, 2011). Third, in food and electronics categories, consumers believe user design effectively meets their needs, reshaping perceived product quality and positively influencing purchase intentions (Nishikawa et al., 2017). However, in luxury categories, consumers perceive users as lacking expertise and capability to design high-quality luxury goods, resulting in lower perceived quality and reduced demand for user-designed luxury products (Fuchs et al., 2013).

3.2.2 Power Mechanism

From a power perspective, feelings of empowerment, corporate identification, and autonomy needs serve as specific psychological mechanisms. First, based on social identity theory, consumers view users as their in-group. User design empowers users to design corporate products, creating a sense of indirect empowerment that strengthens corporate identification and increases preferences for user-design firm products (Dahl et al., 2015). Additionally, user design generates stronger empowerment feelings and corporate identification among low power distance belief consumers. Specifically, low power distance individuals desire equality, and user design grants them power, driving corporate identification and positively influencing their preferences for user-design firm products (Paharia & Swaminathan, 2019; Song et al., 2021). Second, user-design firm products better satisfy autonomy needs of consumers with independent self-construal. When users participate in product design, consumers feel they can autonomously influence corporate production according to personal will and interests, fulfilling autonomy needs and increasing preferences for user-design firm products (宋晓兵 et al., 2017; Dahl et al., 2015).

3.2.3 Psychological Distance Mechanism

From a psychological distance perspective, superiority feelings, self-relevant mental simulation, and self-brand connections serve as specific mechanisms. First, in luxury categories, consumers value professional designers' expertise and status (Moreau et al., 2020). The psychological distance between consumers and users is closer than with distinguished design experts possessing status and wealth. Consequently, user-designed luxury goods reduce perceived product status symbolism, preventing consumers from gaining superiority through social comparison and decreasing purchase intentions (Fuchs et al., 2013). Second, for brand community members, user participation in design narrows the psychological and emotional distance between members and the brand. Through self-relevant mental simulation, information about community users participating in new product design strengthens unique, self-congruent psychological connections, enhancing self-brand connections and increasing brand attachment (王海忠 et al., 2017; 王海忠 & 闫怡, 2018).

3.3 Psychological Mechanisms of AI Design Effects

Consumer reactions to AI design—both positive and negative—can be summarized through value and information mechanisms.

3.3.1 Value Mechanism

From a value perspective, the absence of uniqueness value and emotional value serves as specific psychological mechanisms. AI' s non-human characteristics lead consumers to believe AI-designed products lack uniqueness value in high symbolic value consumption contexts and lack emotional value in luxury contexts. First, in high symbolic value consumption environments where consumers seek to communicate values, abilities, and group membership, consumers believe unique products better express the self. AI-designed products are perceived as less unique than human-designed products, reducing preferences for AI-designed products (Granulo et al., 2021). Second, luxury goods possess both emotional and functional value, though emotional value importance varies across luxury brands. For luxury brands whose essence derives primarily from emotional value, chief designers help create emotional value by providing experiential and symbolic value, whereas AI lacks human emotion comprehension capabilities (Huang et al., 2019). Consequently, consumers perceive AI-designed products as lacking emotional value compared to professional designer products, negatively impacting perceived luxury brand essence and generating negative brand attitudes (Xu & Mehta, 2022).

3.3.2 Information Mechanism

From an information perspective, curiosity serves as a specific psychological mechanism. Relative to professional design, consumers are unfamiliar with AI design and its processes, associating novelty with AI design and stimulating curiosity about it. This curiosity motivates consumers to seek information about AI design and even purchase AI-designed products, further increasing willingness to pay for AI-designed products (Zhang et al., 2022).

In summary, positive reactions to professional design operate primarily through the competence mechanism—professional designers' expertise and authority enhance perceived product quality and corporate trust, particularly among high power distance belief consumers who respect authority. Consumer preferences for user design stem from three factors: First, users' competence performance. Users' numerousness, broad domains, consumer need understanding, fewer constraints, and diversity enhance perceptions of innovation capability, customer orientation, and product quality for user-design firms, though users' limited expertise reduces perceived quality for luxury goods. Second, user design empowers consumers. Granting users design power increases consumers' sense of empowerment, enhances corporate identification, and satisfies autonomy needs of independent self-construal consumers. Third, users belong to the same group as consumers, creating closer psychological distance. For brand community members, user design narrows the distance to the brand, increasing brand attachment. However, for luxury goods, this closer psychological distance prevents consumers from experiencing superiority, generating negative effects. Positive reactions to AI design arise from curiosity about AI design, while negative reactions stem from AI design' s inability to convey certain values. Consumers perceive AI design as lacking uniqueness and emotional value, reducing preferences for AI-designed products in high symbolic value contexts or for luxury brands whose essence derives primarily from emotional value.

4 Boundary Conditions of Source of Design Effect

Whether the source of design effect emerges, its manifestation, and its strength are influenced by consumer, product, and firm factors, as illustrated in Figure 1 [Figure 1: see original paper].

Figure 1 Boundary Conditions of Source of Design Effect

Source: Compiled from literature.

4.1 Consumer Factors

Consumer factors can be divided into individual characteristics, cognitive levels, and perceived psychological distance between consumers and participating users.

4.1.1 Individual Characteristics

Self-construal influences user design preferences. Compared to interdependent self-construal consumers, independent self-construal consumers possess stronger autonomy needs. Since user-designed products satisfy autonomy needs, independent self-construal consumers prefer products from user-design firms more strongly (宋晓兵 et al., 2017).

Power distance belief influences design source preferences. For low power distance belief consumers pursuing equality, user design provides empowerment feelings that satisfy their equality pursuit, driving corporate identification and resulting in stronger preferences for user-design over professional-design products (Paharia & Swaminathan, 2019; Song et al., 2021). However, this effect weakens or reverses for high power distance belief consumers, who believe high-power individuals possess greater decision-making competence. Professional design increases corporate trust for these consumers, generating stronger preferences for professional-design products (Paharia & Swaminathan, 2019; Song et al., 2021).

Need for uniqueness moderates how consumption context symbolic value influences design source preferences. Granulo et al. (2021) found that for high need-for-uniqueness consumers, high symbolic value contexts strengthen preferences for human-designed products, while this strengthening effect is not significant for low need-for-uniqueness consumers. This occurs because consumers perceive human design as unique and AI design as homogeneous, leading high need-for-uniqueness consumers in high symbolic value contexts to prefer human-designed products more strongly.

4.1.2 Cognitive Level

Low user innovation familiarity weakens user design's positive effects. Compared to low familiarity consumers, high familiarity consumers generate more product improvement ideas and better understand user innovation. Schreier et al. (2012) found that high user innovation familiarity leads consumers to project their own abilities or characteristics onto other participating users, believing users possess high design expertise and increasing perceptions of user-design firms' innovation capabilities. Low familiarity consumers are less likely to make such attributions and do not perceive user-design firms as more innovative.

User design effects are stronger for unfamiliar versus familiar brands. Liljedal (2016) found that both brand and user design transmit signals, with brand familiarity determining which dominates. For complex products, familiar brands with good reputations increase brand attitudes and purchase intentions for user-designed complex products. For unfamiliar brands, consumers perceive weak user design capabilities for complex products, reducing perceived innovation capability, brand attitudes, product attitudes, and purchase intentions. For simple products, user design' s positive effects on innovation capability and product attitudes are not significant for familiar brands. For unfamiliar brands, consumers perceive strong user design capabilities for simple products, increasing perceived innovation capability, brand attitudes, and product attitudes.

High AI design knowledge levels weaken AI design' s positive effects. Zhang et al. (2022) found that when consumers possess low AI design knowledge, they exhibit stronger curiosity about AI design compared to professional design, increasing willingness to pay for AI-design firm products. However, when consumers possess high AI design knowledge, curiosity weakens, reducing exploration desire and eliminating significant differences in willingness to pay between professional- and AI-designed products.

4.1.3 Perceived Psychological Distance with Participating Users

For consumers with low perceived similarity to participating users, user design' s positive effects weaken. High perceived similarity activates group identification with the user community, generating stronger indirect empowerment feelings through user participation in corporate product design. This enhances corporate identification and positively influences preferences for user-design firm products. Low perceived similarity prevents group identification and reduces corporate identification, eliminating significant differences in preferences between user-design and internal designer-design firms (Dahl et al., 2015).

Similarly, 王海忠 and 闫怡 (2018) found that non-brand community membership weakens user design' s positive effects. For brand community in-groups, community user participation in design triggers self-relevant mental simulation, enhancing self-brand connections. For out-group non-members, community user participation does not significantly trigger self-relevant mental simulation, preventing self-brand connections.

For mainstream products, perceived similarity with participating users promotes user design preferences. However, for luxury goods, increasing social distance between consumers and user designers can mitigate user design's negative effects. User-designed luxury goods connect luxury brands with users, and socially close users prevent consumers from gaining status-based comparative advantages, negatively affecting preferences. Describing users as groups with social distance from consumers—such as those recognized by professional designers, artists, or celebrities—can reduce user design' s negative effects for luxury goods (Fuchs et al., 2013).

4.2 Product Factors

Product factors can be divided into product category and product characteristics.

4.2.1 Product Category

Luxury goods and their categories influence design source preferences. Consumers believe users lack capability to design luxury goods, that user-designed luxury goods lack status symbolism, and that AI-designed luxury goods lack emotional value, reducing preferences for both user- and AI-designed luxury goods (Fuchs et al., 2013; Xu & Mehta, 2022). However, this negative effect varies by luxury category. For example, compared to leather shoes (high status relevance), athletic shoes (low status relevance) weaken user design' s negative effects because design source minimally impacts perceived luxury quality and status symbolism for low status-relevance luxury goods (Fuchs et al., 2013). Compared to Louis Vuitton (high emotional value importance), BMW (high functional value importance) weakens AI design' s negative effects because consumers perceive AI-designed products as lacking emotional but possessing functional value (Xu & Mehta, 2022).

Utilitarian versus hedonic product categories influence AI design preferences. AI lacks emotional capabilities needed for subjective tasks (Castelo et al., 2019), leading consumers to believe AI cannot perceive their emotional attachment to hedonic products and resulting in lower willingness to pay for AI-designed versus professional-designed products (Zhang et al., 2022). However, concerns about AI's lack of emotion diminish for utilitarian products, and AI excels at evaluating utilitarian attribute values related to facts, rationality, and logic (Longoni & Cian, 2022). Therefore, when utilitarian value is highlighted, consumers show stronger willingness to pay for AI-designed versus professional-designed products (Zhang et al., 2022).

4.2.2 Product Characteristics

High design complexity weakens user design' s positive effects. As design complexity increases, so do required professional knowledge and skills (Schreier et al., 2012). In such cases, users often lack necessary design expertise, leading consumers to rely more on professional designers to ensure design integrity and product experience satisfaction (Song et al., 2021). Schreier et al. (2012) found that for low-complexity products, consumers preferred user-design firm products over internal designer-design firm products, but for high-complexity products, no significant preference differences emerged. 宋晓兵 et al. (2017) and Song et al. (2021) examined how product design complexity moderates effects of self-construal and power distance belief on user design preferences, finding these effects more pronounced for low-complexity versus high-complexity product categories.

High product innovation degree weakens user design' s positive effects. For breakthrough innovations, consumers lack relevant product usage experience and cannot simulate their own design participation scenarios. Compared to corporate design, in-group brand community user design cannot trigger effective self-relevant mental simulation. For incremental innovations, consumers possess relevant usage experience, and community user design can trigger self-relevant mental simulation, facilitating self-brand connections and increasing brand attachment (王海忠 et al., 2017; 王海忠 & 闫怡, 2018). Additionally, when perceived brand product innovation is high, brand community members cannot view participating users as reference groups, preventing self-brand connections. When perceived brand product innovation is low, consumers perceive lower participation costs and reference group effects emerge, making community user participation positively influence self-brand connections and brand attachment (王海忠 et al., 2017).

Low symbolic value products weaken AI design' s negative effects. When consumers purchase high symbolic value products to express the self, their uniqueness motivation is strong, but AI-designed products lack uniqueness, reducing purchase intentions. When purchasing low symbolic value products with instrumental attributes, uniqueness motivation weakens, diminishing (though not eliminating) AI design' s negative effects (Granulo et al., 2021).

4.3 Firm Factors

Choosing selective open user design firms weakens user design' s positive effects. Dahl et al. (2015) found that fully open firms allowing all users to participate more easily activate consumers' user identity, increasing perceived empowerment and corporate identification. Selectively open firms choosing specific users make consumers less likely to connect with participating users, hindering corporate identification. Consequently, consumers show no significant preference differences between selectively open user-design firms and internal designer-design firms. Furthermore, consumer preferences for differently open user-design firms are influenced by power distance beliefs: low power distance belief consumers, pursuing equality, experience stronger empowerment from fully open firms and prefer them, while high power distance belief consumers, trusting authority, perceive selectively open firms as more professional and prefer them (Paharia & Swaminathan, 2019).

In summary, professional design is more popular among consumers when target groups hold high power distance beliefs or when products are luxury goods. Consumers are more likely to prefer products from user-design firms when target consumers have independent self-construal, low power distance beliefs, high user innovation familiarity, brand community membership, and high similarity to participating users, and when product design complexity is low, product innovation degree is low, and firm openness is high. Consumers are more likely to be interested in AI-designed products when target groups are unfamiliar with AI design or when products are utilitarian.

5 Future Research Directions

Previous scholars have primarily focused on product design dimension composition (Homburg et al., 2015; Jindal et al., 2016; Mishra, 2016) and how specific design dimensions influence consumer preferences (Caprioli et al., 2023; Heitmann et al., 2020; Liu et al., 2017; Simonov et al., 2023), without fully exploring how product design source information affects consumer preferences. While product design itself represents a major source of competitive advantage, how firms communicate their design processes also plays a crucial role (Sample et al., 2024). Therefore, understanding the source of design effect can enrich product design communication literature and provide recommendations on when firms should communicate design source information to consumers.

This paper has focused on literature related to the source of design effect, clarified its conceptualization, analyzed essential differences among professional, user, and AI design, reviewed positive and negative consumer reactions to these three sources, and summarized underlying psychological mechanisms—competence for professional design; competence, power, and psychological distance for user design; and information and value for AI design. We also organized boundary conditions from consumer, product, and firm perspectives. Although existing literature has begun exploring the source of design effect, numerous issues require further investigation.

5.1 Investigating Consumer Reactions to Mixed Design Sources

Product design 主要包括开发产品设计方案和选择产品设计方案两个阶段 (Kakatkar et al., 2020). Professional designers, users, and AI can each participate in different design stages. Fuchs and Schreier (2011) experimentally found that compared to firms completing both stages, having users develop designs while professionals select them, or professionals develop while users select them, both improved corporate attitudes and behavioral intentions, though to different degrees. In some cases, consumers reacted more positively to professional design with user selection than to user design with professional selection, but the study did not deeply explore this.

Since professional designers excel at providing solutions while users possess more need information (Moreau & Herd, 2010; Randall et al., 2007), and consumers outperform experts at identifying good product ideas (Kornish & Ulrich, 2014), mixed designs where professionals design and users select may be more favored by consumers for functionally demanding or highly complex products. Future research should deeply examine conditions underlying preference differences for these two mixed design sources. Additionally, professional design with user selection may mitigate negative effects of user-designed luxury goods by respecting professional authority while better satisfying consumer needs. AI design with user selection may compensate for AI' s emotional deficits, reducing AI design' s negative effects. Future studies should explore how other design sources can mitigate negative effects of user and AI design.

In practice, all three design sources can mix in developing or selecting design solutions. For example, in the development stage, professional designers using AI to develop new designs involves both AI analyzing consumer needs through data and professional designers' tacit knowledge (Särmäkari & Vänskä, 2022). In the selection stage, AI helps professionals efficiently screen numerous user design solutions, overcoming subjective biases in user or expert selection (Bell et al., 2024). Whether consumers recognize these mixed design advantages and increase their preferences requires empirical testing. Furthermore, different design sources may design different product parts, such as Xiaomi Band 8 using professional designers for watch faces while inviting users to design wristbands with AI assistance. This mixed approach assigns complex parts to professionals and simple parts to users or AI, potentially mitigating negative effects while leveraging positive effects. Future research should empirically investigate such scenarios.

5.2 Further Investigating Psychological Mechanisms of Source of Design Effect

Existing research has explored multiple psychological mechanisms but overlooked fairness perception. Previous findings on algorithms and fairness perception are inconsistent: some suggest algorithms increase fairness perception while others indicate they decrease it (Bai et al., 2022; Starke et al., 2022). Whether algorithms increase fairness perception depends on decision task characteristics (Lee, 2018; Starke et al., 2022). For instance, Lee (2018) found that in objective tasks, algorithms' objectivity and human managers' authority were perceived as equally fair, while in subjective tasks, algorithms' lack of intuition and judgment made them seem less fair than human managers. However, AI decisions are more accurate than human decisions (Logg et al., 2019; Longoni & Cian, 2022), and AI lacks selfish or benevolent intentions (Garvey et al., 2023), potentially yielding fairer outcomes. Thus, even for subjective tasks, AI may positively influence fairness perception.

Unlike management decisions, product design must balance meeting consumer needs and providing innovative solutions. Whether AI involvement in design enhances fairness perception and influences AI design product preferences, and whether this influence weakens for emotionally-oriented hedonic products or strengthens for fairness-related public goods, warrants in-depth future research.

Both user and AI design influence consumer preferences through multiple mechanisms. Whether product design goals affect which mechanisms dominate deserves investigation. Design goals can be categorized as aesthetic or functional (Althuizen & Chen, 2022). Whether design focuses on aesthetic or functional goals depends on product category and firm design intent. Functional goals demand higher competence, making user design' s competence mechanism more likely to operate. Aesthetic understanding possesses strong social attributes (LaTour & Deighton, 2019; Liu et al., 2017), making user design' s power and psychological distance mechanisms more salient. Functional design is relatively objective, making AI design' s information mechanism more likely to operate, while aesthetic design is relatively subjective, making AI design' s value mechanism more salient. Investigating how design goals affect mechanism dominance can reveal whether consumers more readily accept user or AI involvement in aesthetic versus functional design and under what conditions these design goals better match user or AI design.

5.3 Further Investigating Boundary Conditions of Source of Design Effect

First, from a consumer perspective, future research should examine how uncertainty avoidance—a cultural value—influences the source of design effect. While scholars have studied self-construal and power distance belief effects (宋晓兵 et al., 2017; Paharia & Swaminathan, 2019; Song et al., 2021), uncertainty avoidance remains unexplored. High uncertainty avoidance consumers avoid choices bringing uncertainty or risk (Guo & Wang, 2024) and may prefer widely recognized professional design sources, particularly when purchasing expensive goods. Low uncertainty avoidance consumers are more open to innovation (Kong & Lou, 2023) and may try novel user or AI design. Future research should deeply examine uncertainty avoidance effects and interactions among cultural values like self-construal, power distance belief, and uncertainty avoidance.

Second, from a product perspective, research should examine consumer reactions to product harm crises involving different design sources. As employers of professional designers, firms must take responsibility for designers' work. Consumers may attribute professional design product crises to firms, generating substantial negative impacts. However, crises involving user- or AI-designed products may reduce negative impacts. For instance, 孙乃娟 and 李辉 (2017) found that cooperative customer participation before crises positively influenced forgiveness intentions after crises. As consumer in-group members, user participation creates feelings of indirect involvement (Dahl et al., 2015), potentially strengthening forgiveness intentions and mitigating negative crisis impacts. Additionally, Srinivasan and Sarial-Abi (2021) found that after brand harm crises caused by AI errors, consumers' lower psychological perception of AI agency reduced responsibility attribution for AI-caused harm, resulting in less negative brand reactions. However, consumers more easily lose trust in erring AI and may resist firms' continued AI use for design unless AI demonstrates learning capability (Longoni et al., 2023; Reich et al., 2023). Consumer reactions to product harm crises across different design sources warrant in-depth investigation.

Finally, from a consumption context perspective, research should examine gift-giving contexts. Unlike self-purchase, gift-givers aim not only to satisfy recipients' preferences but also to signal relationship quality (Liu et al., 2019), with gift uniqueness signaling relationship closeness (Goodman & Lim, 2018). AI-designed products lack uniqueness (Granulo et al., 2021), potentially reducing their likelihood of being selected as gifts. Gift-givers also wish to convey love and care (Givi et al., 2023), but AI-designed products may fail to transmit these emotions, negatively affecting preferences. Gift-giving involves high social risk, leading givers to choose higher-priced, more thoughtful products to reduce this risk (Moreau et al., 2011; Wang & Van Der Lans, 2018; Yin et al., 2020). Compared to professional designers, users lack design expertise and skills, making user-designed products less effective at reducing social risk and potentially decreasing gift-giver preferences. Whether gift-givers trust professional designers' capabilities more, believing professional design offers better quality and status symbolism to more effectively reduce social risk and signal relationship quality, thereby rejecting user- and AI-designed products as gifts, deserves further investigation.

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