Investigating Consumer Responses to AI- versus Human-Designed Fashion Products: A Mind Perception Theory Perspective

A Dissertation

SUBMITTED TO THE FACULTY OF THE

UNIVERSITY OF MINNESOTA

BY

Garim Lee

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

Advisor: Dr. Hye-Young Kim

May 2023

Acknowledgments

I would like to express my sincere and deepest gratitude to Dr. Hye-Young Kim, my advisor and mentor throughout my graduate training, for her endless support, trust, and enthusiasm. Her academic, emotional, and professional encouragement has kept me motivated and convinced, which made me grow as a researcher and teacher. I am extremely grateful to my committee, Dr. Hyunjoo Im, Dr. Naeun Lauren Kim, Dr. Xiaoou Li, and Dr. Jean McElvain. They were always there willing to help me and support my research, without which my journey would not have been possible. My gratitude extends to Dr. Claire Segijn, who has taught me invaluable academic courage and passion. I was fortunate to have their mentorship. I cannot fully express my gratitude to them in words. Also, many thanks to Design Graduate Program for the Research and Creative Scholarship Grant.

I would like to send my appreciation and love to my family and friends. My beloved husband, Moon-ki Choi, I could not have done this without you. I am blessed to have you in my life. I deeply thank my mom, dad, and grandmother for their continuous support and encouragement. My dissertation is dedicated to my grandfather in heaven, who always showed me unwavering belief in me.

Abstract

Generative AI, which creates original content based on input data, is becoming prevalent in the consumer environment. The fashion industry can benefit from generative AI, making the overall product design process more efficient and cost and time effective. However, not many studies have investigated how consumers evaluate AI-designed fashion products. The theorization of how consumers perceive AI in the fashion design process is also not yet sufficient. Building on mind perception theory, this study aims to fill the research gaps by examining how consumers evaluate AI's mental and intentional abilities and respond to AI-designed versus human-designed fashion products.

Consumers' negative bias toward AI-designed (vs. human-designed) fashion products is confirmed across the two online experiments (Study 1: n=289; Study 2: n=289). Such effects are explained by perceived experience, perceived agency, and perceived design expertise, while the roles of perceived agency and design expertise are especially prominent. The advantageous effects of humans over AI as design entity are generally confirmed across different product types in the same product categories and perceived threats from AI. Finally, incorporating human aspects when introducing products designed through AI-assisted processes alleviates consumers' negative responses. Varying levels of human aspects in AI applications (AI vs. humanized AI designer vs. human-AI collaboration) lead to different ratings between mind perception, perceived design expertise, and consumer responses. The study contributes to the understanding of the applications of generative AI in retail, focusing on the fashion design process. The theoretical and practical implications are provided drawn from the study findings.

Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

Chapter 1 provides a background on the research topic: AI-designed fashion products. After the problem statement is addressed, a perspective on the problem is described to briefly introduce the theoretical framework and conceptual model of the study. Next, the purpose and the significance of the study are specified. The operational definitions of the primary terms are provided at the end.

1.1 Background

Artificial intelligence (AI) is transforming almost every facet of human life, eventually yielding the creepy fancies of AI singularity—the hypothetical tipping point when AI surpasses human intelligence (Chalmers, 2016). Despite controversial viewpoints on whether the tipping point is likely or not, it is true that AI is exponentially advancing to carry out the tasks that humans used to do in the past. AI refers to a data-driven technique to make intelligent decisions for a given task using a computer (Rodgers, 2021). In recent years, technological innovations have dramatically advanced AI's capacity of ingesting, processing, and analyzing vast amounts of data. Currently, AI can conceptualize the complex relationships among the data, learn the data patterns, and forecast future events in a pre-determined and systematic manner. With such unparalleled power, AI is truly revolutionizing various academic and industrial fields including healthcare, automobile, finance, education, and entertainment. A recent industry report showed that the global AI market share is expected to hit $1,597 billion by 2030 from $119 billion in 2022, indicating an impressive compound annual growth rate of 38.1% (Precedence Research, 2023).

1.1.1 AI in Retail

AI is substantially and aggressively reshaping the retail landscape. Retail is expected to remain the largest U.S. industry for AI adoption until 2025 and drive the growth of the global AI market in the forthcoming years (Precedence Research, 2023; Shirer, 2022). Technologies driven by machine learning, a type of AI that allows computers to learn rules from data examples and predict outcomes with high accuracy without explicit programming (Ding et al., 2018), are redefining retail in various realms from product manufacturing optimization to customer service automation (Guha et al., 2021). For example, within supply chain management, AI-powered demand forecasting allows managers to oversee the inventory levels of business and optimize replenishment much more efficiently than in the past (Cao, 2021). Leading technology firms such as Microsoft and Logility develop and market software for AI-based supply chain solutions. A McKinsey report estimated that such AI-enabled supply-chain management programs helped adopters improve logistics cost efficiency by 15%, inventory levels by 35%, and service levels by 65% compared to competitor companies (Alicke et al., 2021).

Furthermore, it is now considered the new normal for retailers to collect and analyze consumer data and provide personalized and disruption-free services using AI technologies (Hoffman et al., 2022; Kumar et al., 2021). E-commerce companies customize their website layout to show products with a good fit by using individual customers' purchase history and online behavioral data, which promotes seamless consumer journeys and increases conversion rates. AI-powered virtual service agents such as Alexa or chatbots offer enhanced digital experiences for consumers and significantly reduce customer care costs by processing text or voice input, constructing

proper responses, and responding to consumer inquiries (Mariani et al., 2023). Using AI-based prediction, retailers programmatically send personalized advertising through various channels such as Facebook or YouTube to attract new customers. For example, IBM launched Watson Advertising Accelerator to offer retailers AI solutions to optimize one-to-one advertising, leveraging machine learning and real-time consumer data.

Retailers' adoption of AI is not limited to online environments; it also brings technological advancement to brick-and-mortar stores. For instance, AI-enabled checkouts help consumers save the time and energy of checking out (e.g., waiting and scanning products) by automatically recognizing merchandise types and quantities, fostering a frictionless in-store shopping experience (Cui et al., 2022). Amazon Go provides AI-enabled automated checkout services that leverage ceiling cameras, weight sensors on shelves, AI to detect items, and payment information connected to Amazon accounts. Customers can just put items into their carts and exit the store (Ryan, 2021).

1.1.2 Generative AI in the Fashion Product Design Process

Moving beyond the aforementioned practice of calculation and prediction, the current state-of-the-art AI technologies can generate original content, which is termed generative AI. Generative AI refers to the AI that can generate novel or original content based on input data, rather than simply analyzing existing data (Murphy, 2022). For example, an AI research company Open AI's AI language model GPT-4[1] can produce original texts responding to users' text-based prompts and its dataset. Machine-learning-based generative AI is proven to be capable of creating art pieces such as paintings,

[1] https://openai.com/research/gpt-4

images, music, and book scripts (Anantrasirichai & Bull, 2022; Hong et al., 2022) as well as commercial products such as AI-generated ads and the appearance of virtual influencers (Campbell et al., 2022; Wu & Wen, 2021; Wu et al., 2022). For example, DALL·E[2], a system developed by OpenAI, generates digital images from text descriptions using a dataset of text-image pairs. Recently, an AI-generated art picture won an art competition (Roose, 2022), making AI's ability to create art a hot topic of conversation around technology and art. Furthermore, synthetically generated ads are created by altering existing images and videos using deepfakes, a sophisticated media manipulation technique (Campbell et al., 2022). Virtual or computer-generated images (CGI) influencers (e.g., Japan's Imma[3], USA's Lil Miquela[4], Korea's Rozy[5]) are generated by deepfake techniques (Shin & Lee, 2020) and used for many brands' ads online (Thomas & Fowler, 2021). Generative AI is even becoming ubiquitous in the consumer environment; for example, a popular AI-generated video 'Harry Potter by Balenciaga' on YouTube is deemed to show an opening of AI pop culture (Chayka, 2023). Figure 1 shows a few examples of creative works generated by AI.

[2] https://openai.com/dall-e-2/
[3] https://www.instagram.com/imma.gram/?hl=en
[4] https://www.instagram.com/lilmiquela/?hl=en
[5] https://www.instagram.com/rozy.gram/?hl=en

Figure 1

AI-Generated Creative Works

Note. Left: an image generated by DALL·E; Middle: Jason Allen's art piece that won a prize, generated by AI; Right: Japan's computer-generated virtual influencer Imma

The ability of generative AI to accomplish complex tasks such as the creation of original content can be applied to consumer product design, including fashion design. Algorithms can learn a specific aesthetic pattern by analyzing numerous data and create new designs in compliance with the learned aesthetics (Anantrasirichai & Bull, 2022; Harreis et al., 2023; Xian et al., 2018). In particular, generative adversarial networks (GAN)-based generative design is a fast and cost-effective design exploration process to search for design possibilities or optimizations and make original, synthetic content (Hopkin, 2023; Goodfellow et al., 2020; Li & Lachmayer, 2018). Generative design is used in various areas including consumer product design, architecture, construction, engineering, furniture, and manufacturing. By leveraging the generative design process and the capability of AI to design, companies can create new designs for their products efficiently and effectively (Helfrich, 2022; Lee, 2022; Xu & Mehta, 2022). When fashion companies set design goals and pre-determined parameters such as textiles, materials, manufacturing methods, time, and cost in generative design software, the software

utilizes machine learning techniques to explore design alternatives for new fashion products.

Indeed, practitioners across product categories are moving to adopt AI for their product design process taking advantage of generative design. For example, graphic designer Nikolay Ironov[6] who designed commercial logos and products for a year turned out to be a generative design system developed by a design firm. A famous industrial designer Philippe Starck[7] collaborated with furniture company Kartell[8] to create AI-designed chairs. Nathan Shipley[9], a creative technologist working for BMW[10], is using AI to generate new, inspirational car surface designs for BMW 8 Series Gran Coupe based on massive amounts of historical art data. AI is also capable of designing product packaging. Ferrero[11] collaborated with an ad agency Ogilvy & Mather to design Nutella jars packaging using AI. Seven million Nutella jars with AI-designed unique patterns and colors were sold in Italy within a month (Sen, 2017).

Fashion products are also designed using the assistance of AI-generated design alternatives. Collaborating with the artist Robbie Barrat[12], the fashion brand Acne Studios showcased their new apparel designs generated by GAN in Paris Fashion Week 2020 (Papagiannis, 2020). A global clothing company Levi Strauss & Co[13]. utilizes AI to create new denim jacket designs while optimizing production and manufacturing processes. More recently, in New York Fashion Week 2022, the fashion brand

[6] https://ironov.artlebedev.com/
[7] https://www.starck.com/a-i-for-kartell-by-starck-powered-by-autodesk-kartell-p3534
[8] https://www.kartell.com/us/en/ktus/shop/product/a-i-2-sedie/kar05886bi
[9] http://www.nathanshipley.com/
[10] https://www.bmw.com/en/innovation/creative-ai-bmw-8-gran-coupe-art-with-artificial-intelligence.html
[11] https://www.ferrero.com
[12] https://robbiebarrat.github.io/
[13] https://www.levistrauss.com/2021/11/10/ai-shaping-design-levi-strauss/

Greedilous showed off the collection designed by an AI designer named Tilda, developed by LG (Ting, 2022). As AI is bringing innovation in the digital transformation of product design process by analyzing consumer data and generating successful design alternatives (MIT Technology Review Insights, 2021; Young Entrepreneur Council, 2023), the use of AI in design is expected to become more prevalent. Figure 2 presents the industry examples of AI applications in the design process across product categories.

Figure 2

Examples of AI Applications in Product Design

Note. Left: Kartell and Philippe Starck's A.I. chair designed by AI; Middle: Acne Studios and Robbie Barrat's AI-designed clothing in Paris Fashion Week 2020; Right top: Nutella packaging designed by AI; Right bottom: BMW 8 Series designed by AI

1.2 Problem Statement

With the high rate of AI utilization in retail and the technological innovation to create original content using input data, AI is now used to generate new consumer product designs. Indeed, AI applications in product design have become promising and companies are gradually adopting generative design systems. However, although many

recent studies have consistently explored AI applications in retail focusing on consumer receptivity to AI in retail, not much research has investigated how consumers evaluate AI-designed fashion products. Compared to human-designed products, how do consumers evaluate AI-designed fashion products? Do consumers form different attitudes toward fashion products that AI versus human design? Understanding consumer responses to AI-designed fashion products is essential for managers to have the agility to be ready for any unanticipated circumstances that AI-generated creative content as well as AI-led fashion product design would face.

Also, the theorization of how consumers perceive AI in the fashion product design process is not yet sufficient. Do consumers form a specific perception of AI? If so, how does the perception affect the perceived role or capability of AI in the fashion product design process? Researchers have recently explored how consumers perceive AI and AI-enabled services in the consumer environment (e.g., Longoni & Cian, 2022; Longoni et al., 2019; Park et al., 2021; Zhu et al., 2022). However, to the best of the author's knowledge, little empirical evidence exists on consumer perception of AI in the production stage, especially in the fashion product design phase. A more in-depth understanding of how consumers view the potential of AI in fashion product design is necessary because it can benefit retail researchers and practitioners by offering insights into the basis of consumer behavior in response to AI-generated creative works within retail.

Next, what factors will affect how consumers respond to AI-designed fashion products? If consumers differently evaluate AI-designed fashion products versus human-designed ones, what boundary conditions can change the particular responses to AI-

designed products? The findings of the recent studies can provide the initial cues to answer this question; consumers may show different receptivity to AI-made decisions depending on task characteristics (e.g., Granulo et al., 2021; Longoni & Cian, 2022; Zhang et al., 2022) or consumer characteristics may differently affect the responses (e.g., Chinchanachokchai et al., 2021; Smith et al., 2022). Exploring such boundary conditions is especially crucial because it can prepare researchers and practitioners for context-dependent consumer behaviors facing generative AI in the fashion industry.

Lastly, it is important to test how incorporating human aspects into the AI-assisted fashion design process impacts consumer responses to the designed product. As mentioned above, generating original designs using generative AI does not necessarily mean that AI conducts the whole process from zero to one. Algorithms need input data and resource information (e.g., design goals, time and cost constraints, materials, and manufacturing methods) that humans enter as parameters to generate new designs. Suppose retailers emphasize the role of AI and human involvement differently while introducing their AI-assisted design processes to consumers. Then, how will consumers' evaluation of the designed product and overall design process be affected?

1.3 A Perspective on the Problem

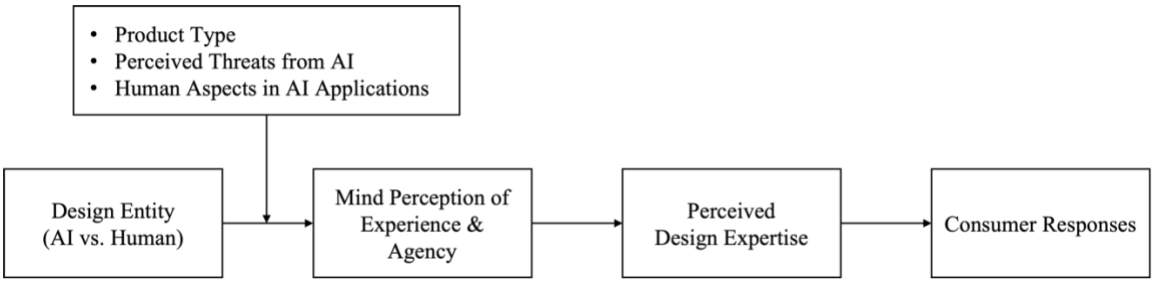
This study draws on mind perception theory to investigate consumer responses to the fashion product that is described to be designed by AI versus human designers. According to mind perception theory, individuals ascribe minds to other entities and determine that entity's state of mind along with two dimensions: experience and agency (Gray et al., 2007; Srinivasan & Sarial-Abi, 2021). Experience is the perceived capacity

to feel and sense pain, pleasure, and emotions, whereas agency is the perceived capacity to act, plan, and exert self-control (Epley & Waytz, 2010; Gray et al., 2007).

Humans are capable of ascribing minds to nonhuman entities. Thus, consumers will ascribe certain levels of mind to AI, which are likely to differ from the inferred mind perception of human designers along with experience and agency dimensions. Such different mind perceptions of AI and human designers are expected to distinguish subsequent perceptions of design expertise and, consequently, the evaluations of the designed fashion products. Moreover, the boundary conditions are proposed based on mind perception theory. Given that mind perception is expected to account for how consumers evaluate the product designed by AI versus human designers, product type (self-expressive vs. functional), consumers' perceived threats from AI, and human aspects in AI applications are expected to differently trigger the effects of the design entity (AI vs. human) on consumer responses by altering the effect of mind perception of design entity. The conceptual model of the study is shown in Figure 3.

Figure 3

Conceptual Model



1.4 Purpose of the Study

The purpose of the study is to fill the research gap by answering the following threefold research questions. First, how do consumers evaluate AI-designed (vs. human-designed) fashion products? (RQ1) This study answers RQ1 by investigating consumer evaluation of AI-designed fashion products compared to human-designed products under the umbrella of mind perception theory. Based on the literature, it is expected that consumers will infer a lower level of experience and agency to AI compared to human designers, which is likely to impact how perceivers evaluate subsequent behavior of the perceived entity. Thus, the difference in mind perception of AI and human designers is likely to impact consumers' responses to products. In this vein, this study aims to test the effects of design entity (AI vs. human) on consumer responses to fashion products and test the role of mind perception of design entity in explaining the effect.

Second, how do consumers perceive the capability of AI in the fashion product design process? (RQ2) If consumer responses to products differ depending on the given information of who designed the products (AI vs. human), and if the mind perception of design entity affects such contrasting responses, it is critical to unveil the underlying mechanism that explains the relationship between mind perception and consumer responses. To answer RQ2, this study examines the mediating role of perceived design expertise between mind perception of design entity and consumer responses to the designed fashion products. Also, this study tests if mind perception and perceived design expertise serially mediate the design entity – consumer responses relationship.

Third, what boundary conditions may alter the effects of design entity on consumer responses to the designed fashion products? (RQ3) Building on mind

perception theory, the structure of generative design, and the existing literature on consumer perception of AI, this study examines the moderating effects of product type (self-expressive vs. functional), consumers' perceived threats from AI, human aspects in AI applications in the relationship between design entity and consumer responses. Further examination of the context-dependent role of mind perception is beneficial to understanding the effects of design entity. All research questions are presented in Table 1.

Table 1

Research Questions

RQ1	How do consumers evaluate AI-designed (vs. human-designed) fashion products?
RQ2	How do consumers perceive the capability of AI in the fashion product design process?
RQ3	What boundary conditions may alter the effects of design entity on consumer responses to the designed fashion products?

1.5 Significance of the Study

This study is one of the theoretically novel research studies that can provide meaningful contributions to existing knowledge. First, the study findings can improve the knowledge of AI-generated original work from the standpoint of retail studies by examining how consumers evaluate AI-designed fashion products compared to human-designed products. Previous research (e.g., Agudo et al., 2022; Chamberlain et al., 2018; Ragot et al., 2020) has continuously explored the human perception of AI-generated creative work, mainly focusing on art and music. There have been mixed findings on how

people evaluate AI-created artworks. While many studies (e.g., Ragot et al., 2020) found negative perceptions toward AI-created artworks, others (e.g., Hong, 2018) suggested that such negative perception does not necessarily hold true. Taking it to the retail and fashion level, this study broadens the area of AI applications in art creation to consumer product design. By adding empirical evidence to the previously reported mixed findings, the current study will provide further comprehension of the topic in the context of designing consumer products.

Second, this study contributes to the knowledge regarding consumer perception of AI technologies from the perspective of mind perception theory. Investigating the mind perception of design entity (AI vs. human) could offer an in-depth understanding of why perceived design expertise and responses to the designed fashion products are consequently affected. Also, the findings will help understand how mind perception impacts consumers' resistance or acceptance of AI-enabled automation in various retail industries. The comparison of mind perception of AI versus humans will advance the knowledge of not only product design but also other tasks that both AI and humans can conduct, such as consumer service and product recommendation.

Third, this study explores under what circumstances consumers' evaluation of AI-designed fashion products can be altered. Understanding the influence of product type and consumers' perceived threats from AI affecting AI acceptance or resistance provides structured insights into how AI can be well utilized depending on companies' goals. As some researchers (e.g., Huang & Rust, 2022; Longoni & Cian, 2022; Noble et al., 2022) recently stressed, emphasizing the joint effort of AI and humans rather than considering AI to work on behalf of humans would be the correct direction in the midst of AI

proliferation. Especially in the design industries, it is a dominant view that AI supports humans (not replacing humans), although AI conducts the major creation works. The current study's findings on the moderating roles of product type, consumer characteristics, and human aspects in AI applications in the relationship between design entity and consumer responses will add a nuanced layer to the empirical evidence of the contextual components affecting consumer responses to AI-assisted design process.

From a managerial perspective, the study findings on consumer responses to AI-designed fashion products are useful for companies that look forward to taking advantage of generative design in the product design stage. The effectiveness of utilizing AI in the design process is evident. Algorithms help human designers explore myriad design possibilities time-efficiently, which in turn reduces the costs of production and benefits consumers. Thus, moving beyond the domain of AI-generated creative artwork, more profound knowledge of how consumers evaluate AI-designed fashion products will be helpful for companies to keep these advantages by stably progressing the use of AI.

Second, the current study designed to demonstrate how consumers perceive the capability of AI compared to humans in the fashion product design process is beneficial for retailers. This is because the study findings provide business acumen about the plan for the growth of AI applications in other production stages as well as for the use of generative design. The findings on the perception of design entity, such as two distinct mind perceptions (i.e., experience and agency) and perceived design expertise, will help grasp how to properly and effectively employ the roles of AI and humans in the production stage.

Lastly, the investigation of product type, consumer characteristics, and the extent to which the human aspect is incorporated in the AI-assisted fashion product design process affects consumer responses could offer valuable practical guidance. The findings suggest retailers constructive tips on how to suitably adopt generative design systems and how to cleverly communicate with consumers when introducing their strategies. Moreover, human designers can have insights into the evolving roles of human designers by understanding how consumers perceive humanized AI designer or human-AI collaboration compared to sole AI or human designers.

1.6 Operational Definitions of Terms

Algorithm appreciation: The phenomenon of people preferring algorithm decisions to human decisions (Logg et al., 2019)

Algorithm aversion: The phenomenon of people preferring human decisions to algorithm decisions and being reluctant to accept algorithm decisions (Dietvorst et al., 2015).

Artificial Intelligence (AI): A system's ability to continuously collect and learn from data and solve new problems in an ever-changing environment with the purpose of achieving specific goals (Cao, 2021; Kaplan & Haenlein, 2019).

Experience gap: The finding that humans are perceived to be significantly more capable of experiencing emotion and sensation than are robots and other machines (Gray & Wegner, 2012).

Generative AI: The types of AI that can generate new, novel, or original content based on input data and the patterns of the data, instead of simply analyzing existing data (Murphy, 2022).

Generative design: A cost-effective machine learning technique based on algorithmic and parametric modeling used to explore design possibilities or optimizations (Li & Lachmayer, 2018).

Machine learning: A type of Artificial Intelligence that allows computers to learn rules from input data and predict future patterns or outcomes with high accuracy without explicit programming (Ding et al., 2018).

Mind: A capacity to think, feel, and engage in willful action (Tharp et al., 2017).

Perceived agency: The perceived capacity of an entity to be an autonomous agent, such as act, plan, self-control, and thought (Gray et al., 2007).

Perceived experience: The perceived capacity of an entity to feel emotions, such as pain, pleasure, and hunger (Gray et al., 2007).

Theory of mind: The ability to infer mental states to oneself and other entities in order to predict and explain behavior (Premack & Woodruff, 1978).

Chapter 2. Literature Review

Chapter 2 provides the foundational information for this study by reviewing previous research. First, the definition of AI is discussed, followed by a review of the literature on AI applications in retail. Second, the existing literature on consumer responses to AI's creative works is reviewed and evaluated. Third, the unique characteristics of the product design process in the field of fashion is presented. Next, the mind perception theory is discussed as the theoretical underpinning of this study. Finally, the last section delineates how hypotheses are established based on the literature review to answer the research questions, showing the research model of this study.

2.1 Background Literature

2.1.1 Definition of AI

Before delving into the review of related research, what exactly is AI? Despite the ever-ascending growth in AI implementation, a clear-cut consensus lacks on how AI can be precisely defined across domains; there has been a continuous debate about the single definition of the term since first introduced. The term *artificial intelligence* was coined by John McCarthy, a professor emeritus in computer science at Stanford, in 1955. The initial definition was "science and engineering of making intelligent machines" (McCarthy, 2007, p. 2). However, descriptions of AI have become vary across different domains as technological development allowed applying AI to multifarious works. AI is considered, in a broad sense, an umbrella term covering a number of technologies and analysis methods. In this view, AI refers to a collection of innovative technologies with the purpose of simulating human intelligence, especially for cognitive tasks such as problem-

solving (Russell, 2010; Qin & Jiang, 2019). In addition to cognition-related tasks, some view AI to have abilities to emulate skills inherent in humans, for example, thinking, feeling, and executing physical or mechanical tasks (Huang & Rust, 2021). While multiple definitions of AI exist, the most commonly shared concept is that AI is a data-driven technique for making intelligent decisions using a computer (Rodgers, 2021).

One of the most frequently accepted definitions of AI in consumer studies was proposed in Kaplan and Haenlein's (2019) work (Davenport et al., 2020; Guha et al., 2021). The authors defined AI as a system's ability to correctly interpret data, learn from the interpretation, and achieve given tasks through the flexible adaptation of the learnings. Furthermore, Cao (2021) expanded the definition of AI for retail by incorporating the concepts of *adaptation in ever-changing environments* and *continuous collection of data*, considering the constantly changing retail environment. Thus, in line with the existing literature, this study adopts the conceptualization of AI as a system's ability to continuously collect and learn from data and solve new problems in an ever-changing environment to achieve specific goals (Cao, 2021; Kaplan & Haenlein, 2019).

2.1.2 AI Applications in Retail

The accelerated implementation of AI is constantly and dramatically transforming the retail industry. By utilizing cutting-edge AI technologies, retailers have improved productivity and optimized business operations more effectively. To understand this phenomenon and help shape the future trajectory of AI applications, researchers have increasingly paid attention to AI (e.g., Davenport et al., 2020; Loureiro et al., 2021; Mariani et al., 2023). Applications of AI in retail include diverse sectors, for example,

personalization and recommendation systems, frontline customer service, customer relationship management, supply chain optimization, and in-store task management (Shankar et al., 2021). Shankar (2018) categorized the ways in which AI is used in retail, based on whether AI applications are customer-facing or non-customer-facing (Guha et al., 2021; Shankar, 2018), suggesting *consumer-side* and *supply-side* applications. This study's topic, consumer responses to AI-designed products, is more related to customer-facing aspects (i.e., consumer-side applications). Thus, the following sections review the existing literature on consumer-side applications of AI.

Consumer-side applications include (a) understanding/anticipating omnichannel/mobile shopping behavior, (b) personalization and recommendation services, (c) sales management and customer relationship management (CRM), (d) in-store customer experience management, (e) customer service and payment management, and (f) media optimization. Leveraged by the system's power to analyze consumer and business data and predict future events, these AI applications aim to provide optimal alternatives to consumers. First, AI is used to understand behavioral patterns of omnichannel and mobile shoppers and offer a better customer experience. Consumers' omnichannel behavioral patterns are key to understanding overall shopping behavior and determining future purchases across channels (Chang & Li, 2022; Gao et al., 2022). However, omnichannel strategies successfully connecting multiple channels have been difficult to achieve yet (Neslin, 2022). Thus, retailers are endeavoring to deliver improved omnichannel service as well as analyze omnichannel/mobile consumer data using AI. A few studies found that AI-powered omnichannel services are beneficial for

value co-creation (Payne et al., 2021) and for enhancing consumer experiences (Sung et al., 2021).

The second AI applications type, personalization and recommendation services, is one of the most popular and currently active areas where AI is used in retail. Retailers recommend personalized content or services to their customers by harnessing the ability to gauge individual preferences and predict next purchases (Gauri et al., 2021; Marchand & Marx, 2020). For example, Netflix is well known for providing content recommendations by analyzing the watching history and search terms of over two hundred million users. Much research explored the consequences of AI-powered personalization and recommendation services, confirming both advantages and drawbacks or dilemmas of the services (Ahn et al., 2021; Gao & Liu, 2022; Longoni et al., 2019; Longoni & Cian, 2022).

Third, AI is used to identify new sources of revenue and implement beneficial customer relationship management (CRM) tactics (Shankar, 2018). Retailers can spot new target segments and interact with customers using AI's analytical power. Libai et al. (2020) proposed that AI-embedded CRM strategies can improve the ability to predict customer lifetime value and may lead to greater customer prioritization and service discrimination in markets. While a few researchers found that AI helps increase the effectiveness of CRM programs (e.g., Menidjel et al., 2022), empirical findings to date on the positive effect of AI-embedded CRM strategies powered by AI are yet not substantial. In addition to formal AI-embedded CRM programs, AI-powered services such as conversational agents can positively impact consumer engagement and loyalty (Huh,

Kim, and Lee, 2023; Mariani et al., 2023), whereas it may backfire in case consumers perceive higher risk from the automated services (Hasan et al., 2021).

Retailers utilize AI to enhance the customer experience in physical stores effectively. AI-based humanoid service robots, defined as system-based autonomous and adaptable interfaces that deliver service to customers (Wirtz et al., 2018), interact with consumers and provide unprecedented customer experience. For example, at a home improvement retail company Lowe's, LoweBot[14] assists consumers by helping them find items and answering simple questions (Forgan, 2020). Because in-store service robots have appearances, research has examined the effects of robot appearance on consumer responses as well as determinants and consequences of service robot adoption (Choi et al., 2021; Song & Kim, 2022; Zhang et al., 2021). Furthermore, AI allows seamless checkout services with which consumers can skip the hassles of waiting in a queue and scanning products while checking out. It was proven that the AI-enabled checkout is useful to derive favorable consumer responses such as positive evaluation of store atmosphere and higher purchase intention (Cui et al., 2022; van Esch et al., 2021a, 2021b).

Customer service is one of the top areas where AI is highly effective in retail. In addition to in-store service robots, text- and voice-based agents such as chatbots and voice assistants provide customer service without time and place restrictions, yielding a robust customer experience (Cao, 2021). Some research has investigated consumer perceptions and consequences of AI service agents (e.g., Lou et al., 2022; Tran et al.,

[14] https://www.lowesinnovationlabs.com/projects/lowebot

2021; Whang & Im, 2021), often compared to human employees. Comparison between AI agents and human employees was possibly because customer service was mainly executed by humans before the development of AI. The other group of research focused on the context of AI agents' service failure (Choi et al., 2021; Huang & Dootson, 2022; Mozafari et al., 2022). Furthermore, AI can be used for fraud detection services, for example, using a deep learning model to detect and prevent transaction and consumer fraud proactively (Knuth & Ahrholdt, 2022; Shankar, 2018). However, not many empirical studies have been conducted in the consumer studies area.

Lastly, retailers are increasingly using AI to optimize their digital media communication. For example, a cloud-based AI platform Albert[15] help companies optimize cross-channel campaigns by targeting audiences and running campaigns across paid and earned media channels such as YouTube and Facebook. Furthermore, retailers use AI-enabled programmatic advertising, where automatic bidding systems are used to target consumers online with context-aware advertisements (Deng et al., 2019; Yun et al., 2020). Researchers have conceptually and empirically explored consumer responses to or consequences of AI-enabled media communication optimization strategies (Bakpayev et al., 2022; Ciuchita et al., 2022; Wu & Wen, 2021; Wu et al., 2022).

Table 2 summarizes some of the existing studies on AI applications in retail organized by Shankar's (2018) categorization.

[15] https://albert.ai/ai-marketing-software/

Table 2

Types of AI Applications in Retail

Applications	Past studies	Main findings
Understanding / anticipating omnichannel / mobile shopping	Payne et al. (2021)	AI-enabled mobile banking services offer transaction-oriented value propositions more than relationship-oriented value propositions.
	Sung et al. (2021)	AI-embedded mixed reality in the consumption environment can yield immersion, enjoyment, and novel experiences, which enhances consumer engagement, unpaid brand endorsement, and purchase intentions.
Personalization and recommendation services	Longoni et al. (2019)	Consumers are reluctant to utilize healthcare provided by AI due to the concern that AI (vs. human) are less able to consider one's unique characteristics and circumstances.
	Ahn et al. (2021)	Consumers feel more psychologically distant in response to AI recommenders than humans due to a different level of perceived similarity. AI recommendation with secondary (vs. primary) features is more effective when AI is humanized.
	Gao & Liu (2022)	AI-enabled personalization benefits customer journey by manifesting itself as personalized profiling, navigation, nudges, and retention.
	Longoni & Cian (2022)	AI recommenders are perceived to be more competent than humans in the utilitarian realm but less competent than humans in the hedonic realm.
Sales management / CRM	Libai et al. (2020)	Artificially intelligent CRM system results in greater customer prioritization and service discrimination in market.
	Menidjel et al. (2022)	AI-assisted loyalty program enhances customer engagement and loyalty, consequently improving loyalty program effectiveness.
In-store customer experience management	Choi et al. (2021)	Consumers are less satisfied when a service failure is caused by humanoid (vs. nonhumanoid) robots due to different levels of warmth perceptions.
	van Esch et al. (2021a)	AI-enabled (vs. self-service) checkouts activate perceived shopping convenience, resulting in more favorable attitudes and higher purchase intervention for those with high self-efficacy.

	van Esch et al. (2021b)	AI-enabled (vs. self-service) checkouts lead to higher consumer patronage likelihood due to the sensory stimulation from in-store communication. Consumers' perceived threats from AI moderates the effect.
	Cui et al. (2022)	AI-enabled checkouts yield more favorable store atmosphere evaluations and higher purchase intention, mediated by heightened arousal.
	Song & Kim (2022)	Perception of usefulness, social capability, and appearance of service robots positively affect attitudes toward human-robot Interaction, consequently predicting expectation of better service quality and higher acceptance.
Customer service and payment management	Tran et al. (2021)	Consumers' overall sentiment are less negative toward a chatbot than a human agent.
	Whang & Im (2021)	Consumers form a more positive perception and evaluation of websites (vs. AI voice assistants) because voice assistants are perceived as pseudo-human agents detached from the service provider.
	Huang & Dootson (2022)	In a chatbot service failure context, letting customers know the availability of human employees late makes customers engage in emotion-focused coping, resulting in customer aggression.
	Lou et al. (2022)	Human employee is perceived to be more competent and warmer than a chatbot.
	Mozafari et al. (2022)	Disclosing the AI chatbot identity negatively affects customer retention due to attenuated trust for services with high criticality. In a chatbot service failure context, disclosing the chatbot identity does not negatively impact but elicits a positive effect on retention.
Media optimization	Wu & Wen (2021)	Consumers' perceived objectivity of the ad creation process decreases perceived eeriness of AI-created ads while it increases consumer appreciation of AI-created ads.
	Bakpayev et al. (2022)	Consumers evaluate Al-created (vs. human-created) ad more negatively when the ad has emotion-oriented content, while they form equally positive attitudes toward human-created and Al-created cognitive-oriented ads.
	Ciuchita et al. (2022)	Consumer attitudes toward programmatic advertising are positively associated with attitudes toward the retailer. The disclosed use of AI for programmatic advertising does not significantly influence consumer attitudes toward programmatic advertising.
	Wu et al. (2022)	According to an analysis of Twitter posts showing people's thoughts about using AI in advertising, "AI-powered marketing tools" is the most positive topic, but "AI's involvement in social media campaigns" is the most negative topic.

2.1.3 Consumer Responses to AI's Creative Works

The technological ability of AI to create original content is rapidly evolving, leveraged by advanced machine learning. Extending such ability to the retail and fashion realm, one of the promising domains in which AI can be used is fashion design. Employing AI for design has been anticipated to benefit companies and consumers by innovating product design processes (Figoli et al., 2022; Liao et al., 2020; Verganti et al., 2020). The idea of AI designing products sounded rather optimistic when Maurice Conti explained the usage of algorithms for product and industrial design in his 2016 TED talk. Nevertheless, as recent industry cases prove (e.g., Philippe Starck's AI-designed chair, Levi Strauss & Co. using AI to design new Levi's® Trucker jacket, BMW using AI to explore 8 Series surface designs), companies are starting to integrate AI into product design processes. As researchers and practitioners claimed, the power of AI to analyze vast amounts of data and expeditiously design options reduces costs and labor-intensive human work but increases time efficiency (Li & Lachmayer, 2018; MIT Technology Review Insights, 2021). Furthermore, AI is expected to allow smooth exchanging of information across the product design process steps, consequently yielding the ability to adapt to market or trend changes (Berisha & Lobov, 2021).

However, although previous research has extensively explored AI applications in retail in diverse contexts, only a few studied consumer responses to AI applications in product design, yielding scattered understanding. Focusing on fashion products, Sohn et al. (2020) examined Gen Y's responses to products designed using generative adversarial network (GAN), an artificial intelligence technology under consumption value theory. Their findings showed that functional, social, and epistemic values positively affect

purchase intention of GAN-generated fashion products, and willingness to pay is significantly higher for GAN-generated (vs. non-GAN-generated) products. More recently, Xu and Mehta (2022) tested how consumers respond to luxury products designed by AI (vs. humans) based on the literature on luxury products' emotional and functional values. Their findings indicate that AI as a design source mainly devalues emotional value and leads to differential effects on perceived brand essence and consumer responses depending on product characteristics (e.g., fashion or automobiles). Zhang et al. (2022) found that Chinese consumers are more willing to pay for AI-designed (human-designed) products because AI-designed products lead to higher curiosity. Their findings also showed the boundary conditions such that willingness to pay for AI-designed products is lower for knowledgeable consumers and hedonic products.

While only a few studies to date explored consumer responses to AI applications in commercial product design, researchers have constantly investigated the role of AI in creative works and people's responses to AI-generated creative works. The studies have mainly focused on the arts and music domains, while the study contexts keep expanding. In the same way that people have mixed feelings about AI technologies (Du & Xie, 2021), mixed results have been obtained on how people perceive and evaluate AI-generated creative works. While people often ascribe the ability to create art to AI (Lima et al., 2021), most studies found that people generally tend to be prejudiced against and discount the works created by AI. For example, Moffat and Kelly (2006) confirmed that people hold a common negative bias against computer-generated music, and such bias was stronger in the musician group than in the non-musician group in their study.

Similarly, Hong and Curran (2019) found that people do not judge human-created and AI-created artworks as equivalent in their artistic value, indicating the relative strengths of human artists. Ragot et al. (2020) examined how people evaluate artworks created by AI versus human artists on four dimensions: liking, perceived beauty, novelty, and meaning. The paintings presented as AI-created (vs. human-created) works were perceived as less beautiful, novel, and meaningful and were significantly less liked by the participants (Ragot et al., 2020).

On the other hand, the other groups of studies have suggested that the negative bias against AI-generated works does not necessarily hold true. For example, under the framework of schema theory, Hong (2018) used focus group interviews to examine whether and how people are biased in ascribing creativity to AI artwork. The results showed that the same artwork is more positively considered to be "art" when it is perceived to be created by humans (vs. AI). However, the participants' end responses to both human- and AI-generated artworks were not significantly different. The authors explained that the results are the products of the different schema; people tend to focus on the interactive view of human artworks but the sensory part of AI artworks. Hong and Curran (2019), who found humans' strengths in perceived artistic value, suggested that different artistic values do not necessarily yield different evaluations of the artwork. Xu et al. (2020) found similar results from machine learning-mixed online experiments. They investigated how people respond to genres and authorship (machine vs. humans) cues of artworks in a cross-cultural context. Their findings showed that people's responses to machine-created and human-created artworks are not significantly different, while genres and cultures have differential effects on responses.

Contrary to the many studies, Lopez et al. (2019) found that human-generated creative works can be less favorably evaluated than the ones generated by AI. Lopez et al. (2019) explored people's biases toward the perceived functionality of machine- and human-created designs using simple boat sketches. In their study, participants perceived sketches generated by a deep learning generative model to be more functional than those drawn by humans. The findings also indicate that people show more negative bias against design works with a "human-generated" label (Lopez et al., 2019).

Table 3 presents the existing literature on consumer responses to AI-generated creative works. In sum, the major research stream supports the view that people generally have a more negative bias against creative works generated by AI than by humans. However, an in-depth review of the related literature revealed mixed findings on how people evaluate AI-generated creative works. Further investigation focusing on context- and product-specific factors is thus called for from diverse theoretical perspectives into how and why consumers perceive and evaluate AI-generated works. Also, the debatable, contrasting findings of whether people prefer creation generated by AI or by humans provide room to investigate the unexplored boundary conditions that alter negative bias toward AI-generated works.

Table 3

Existing Literature on Consumer Responses to AI-generated Creative Works

Studies	Contexts	Main findings
Agudo et al. (2022)	Audiovisual artwork	• People attribute lower sensitivity, lower ability to evoke emotions, and lower quality to the artwork when they are told it is designed by AI (vs. human). • People's different evaluations of artwork designed by AI versus humans are because of, at least in part, stereotypes and biases about the creativity of AI.
Chamberlain et al. (2018)	Artwork	• People hold prejudices against computer-generated (vs. human-generated) art, which is mainly driven by the kind of art that people believe algorithms are capable of producing. • The prejudices against computer-generated art can be alleviated when people infer anthropomorphic characteristics in computer programs.
Hong (2018)	Art paintings	• AI is considered unable to create art because it cannot have a feeling, intention, and the chance of creating mistakes. • People evaluate artworks created by humans and AI regarding expression, creativity, and providing a message similarly. • People focus on an interactive view of human art (perceiving, providing feedback), whereas they focus on the sensory part (visual, auditory) of AI art.
Hong & Curran (2019)	Artwork	• People do not judge human-created and AI-created artworks as equivalent in their artistic value and degree of expression. • Generally, knowing that an artwork was created by AI does not affect the evaluation of the artistic value of the artwork.
Hong et al. (2022)	Music	• AI music generator's human-likeness, but not autonomousness in creating music, make it seen as a genuine musician. • Although the evaluations of AI-generated music are seemingly independent of AI's attributes, people preferred the music from the AI considered as a musician versus a music generator.

Lima et al. (2021)	Art paintings	• Assessing an AI's lack of mind influence how people subsequently evaluate AI-generated art. • Overvaluation of AI-generated images could negatively affect AI's perceived agency. • Interacting with AI-generated art does not affect the morality perception of the machine.
Lopez et al. (2019)	Simple sketches	• According to human participants' responses and computer simulation, computer-generated sketches are perceived as more functional than human-generated sketches. • The perceived functionality of sketches is negatively affected by explicitly presenting them with a label of agency origin, which effect is larger for human (vs. computer) sketches.
Moffat & Kelly (2006)	Music	• People have a common negative bias against computer-generated music, which tendency is stronger for musicians than for non-musicians.
Ragot et al. (2020)	Art paintings	• People prefer artworks presented as created by a human artist to ones presented as created by AI. • Compared to artworks created by AI, those created by a human artist were evaluated as more beautiful, novel, and meaningful.
Raj et al. (2023)	Writings	• AI disclosure does not affect the evaluation of creative or descriptive stories. • However, AI disclosure negatively affects the evaluations of emotionally evocative poems written in the first person. • Negative reactions to AI-generated content may arise when the content is viewed as distinctly "human."
Sohn et al. (2020)	Fashion products	• Willingness to pay is significantly higher for GAN-generated products than for non-GAN-generated products. • Perceived functional, social, and epistemic values positively affect Gen Y's purchase intention of GAN-generated products.
Sun et al. (2023)	Music	• People perceive higher competence from more human-like AI musicians, which is a crucial facilitator of attitudes toward AI musicians. • Perceived warmth helps people form positive attitudes toward AI musicians. • Listening to AI-generated music or not moderates the relationship between the level of anthropomorphism and perceived competence.

Xu et al. (2020)	Art paintings, poems	• People's responses to artworks are independent of authorship cues (AI vs. human artists). • People from different cultural backgrounds assign different discussion topics to artworks created by AI versus humans. • People's technology use experience affects psychological responses; those who interact with AI less often in their daily life tend to express emotional feelings about the artworks more.
Xu & Mehta (2022)	Fashion and automobile products	• Using AI as a design source decreases the perceived emotional value but increases the perceived functional value associated with a luxury brand. • For luxury brands with emotional values (e.g., fashion brands), using AI in the design process generates the perception that the brand is losing its essence, reducing positive brand attitudes and purchase intentions. • For luxury brands with functional values (e.g., automobiles brand), the negative effect of using AI in the design process is attenuated due to the enhanced functional value perception.
Zhang et al. (2022)	Fashion products, mug, painting, lenses	• Consumers' willingness to pay is higher for AI-designed products because of curiosity. • Consumers with higher knowledge are less curious about AI-designed products, decreasing their willingness to pay. • Willingness to pay for AI-designed products is higher for utilitarian products than hedonic products.

2.1.4 Product Design in the Field of Fashion

Before investigating the AI applications in the fashion product design process, it is important to understand the unique nature of fashion products and their product development process. Among the diverse fields with the product design process, the fashion industry is the area that entails exceptional endeavors to generate original, creative designs that distinguish itself from other product categories (Granger, 2015). Fashion refers not only to dresses but also to other accessories, including shoes, shawls, and handbags. As various types of fashion products exist, the fashion design process requires the application of numerous product construction and multifaceted aesthetics (Hopkins, 2021).

Furthermore, fashion design is intricate in that fashion involves both functional features and social and cultural meaning (Lamb & Kallal, 1992). First, functional aspects of fashion products, such as production and communication (Lennon et al., 2017), are considered throughout the design process. For example, materials and patterns of fashion products are designed to protect the body and materials or extend the body's capabilities in surrounding variable environments (Han & Koo, 2014; Koo, 2018; Park et al., 2014). Also, fashion products function to convey information or situationally determined meanings. Fashion designers are thus expected to know how the design elements will perform to communicate desired information, for example, the wearer's role or status in an organization (Nelissen & Meijers, 2011). Second, fashion design requires a comprehension of the psychological, sociological, and anthropological perspectives of the design (Johnson et al., 2014; Lennon et al., 2017). Fashion product is often used as a medium to express self and brand identity (Johnson et al., 2014; Park et al., 2020) or a

tool to perceive or categorize others (Hopkins, 2021; Lennon et al., 2017). Also, specific fashion design can imply certain interpretations, which may vary depending on the culture and context (Jung & Lee, 2009). Thus, fashion design is deemed the art of applying absolute fashion-related knowledge (e.g., clothing construction, textile, technology), aesthetics (e.g., color, pattern, style), and meanings underlying the design elements (e.g., symbolic meanings, cultural appropriateness, impression) to products in the development process.

2.2 Theoretical Framework

Building on the review of the related literature, the formulated research questions of this study focusing on consumer responses to AI applications in the product design process are as follows: How do consumers evaluate AI-designed (vs. human-designed) fashion products? (RQ1); How do consumers perceive the capability of AI in the fashion product design process? (RQ2); What boundary conditions may alter the effects of design entity on consumer responses to the designed fashion products? (RQ3). This study employs mind perception theory (Gray et al., 2007) as the theoretical framework to answer the above research questions.

2.2.1 Mind Perception Theory

Mind perception theory explains that people ascribe minds to other entities and consider the contents of the minds along with the two continuous dimensions: conscious *experience* and intentional *agency* (Epley & Waytz, 2010; Gray et al., 2007). *Experience* is the perceived mental capacity to feel and sense pain, pleasure, pride, and emotions. Not only including affective factors, but *experience* also consists of biological states such as

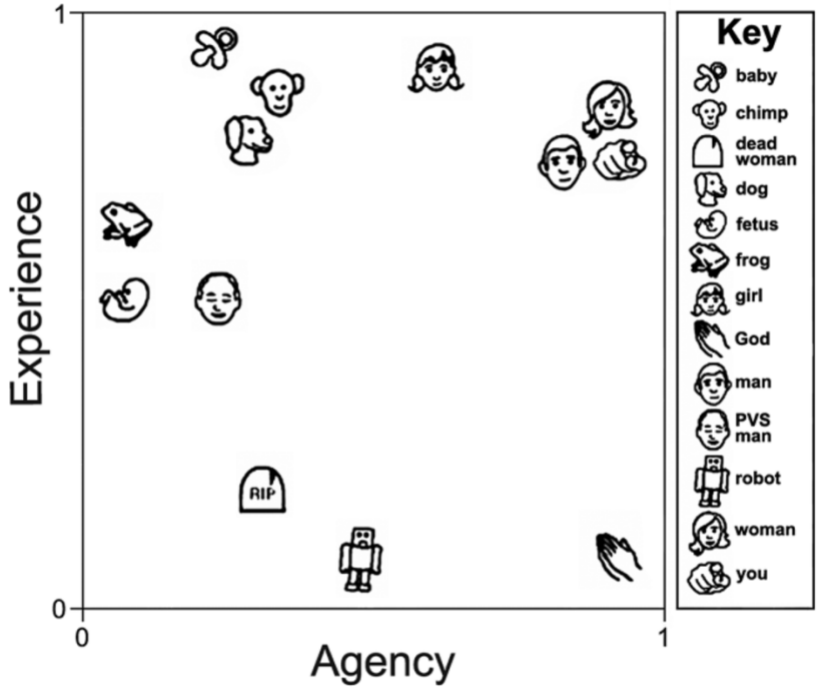
hunger and pain. *Agency* is the perceived intentional capacity to act, plan, and exert self-control. The two mind perception dimensions, experience and agency, can be perceived quite independently (Epley & Waytz, 2010). For example, adults are perceived to have high agency and experience, whereas a baby is perceived to have low agency and high experience, and a robot is perceived to have a moderate level of agency and low experience (Gray et al., 2007). Also, both dimensions tend to correlate with some personal judgments of the character such as liking for the entity and wanting to make it happy (Gray et al., 2007).

How was mind perception theory developed? In the mid-2000s, social psychologists were interested in developing new frameworks of how people understand one another by inferring others' minds. Here, "mind" refers to a capacity to think, feel, and act willfully (Tharp et al., 2017). Until the mid-2000s, the majority of the literature studying attribution of minds was focusing on a theory of mind. A theory of mind was first introduced when Premack and Woodruff (1978) tested whether chimpanzees have a theory of mind. While the term has the word *theory*, theory of mind is not a theory. Instead, "theory of mind" refers to the ability to infer mental states to oneself and other entities in order to predict and explain behavior (Premack & Woodruff, 1978). Early work on a theory of mind identified various indicators but did not categorize whether minds are perceived along multiple dimensions. Gray et al. (2007) believed there would be more than one dimension that people determine others' minds. Therefore, Gray et al. (2007) developed mind perception theory to systematically understand how individuals infer whether others have mental states and with what dimensions they decide what the inferred mental states would be. They conducted web surveys asking 2399 participants to

evaluate various mental capacities of other entities such as living humans (e.g., infant, girl, adult woman and man), nonhuman animals (e.g., dog, frog, chimpanzee), a dead person, God, and a robot. A factor analysis of these mental capacities unveiled that people perceive two dimensions of mind: *experience* and *agency*. Figure 4 shows the mind perception from various entities obtained from Gray et al.'s (2007) study.

Figure 4

Mind Perceptions of Other Entities (Gray et al., 2007)



Note. PVS: persistent vegetative state

2.2.2 Previous Studies on Mind Perception Theory

Researchers have explored mind perception in various settings, as mind perception is not limited to humans or living creatures. It is known that humans have long attributed humanlike minds to nonhuman agents, at least since the sixth century B.C.

(Epley & Waytz, 2010; Lesher, 1992). People can infer minds from nonhuman agents such as animals, gadgets, gods, or machines. Even natural phenomena can be treated as having a mind depending on the context; for example, the north wind and the sun in Aesop's fable have humanlike personalities (Takahashi et al., 2016). Thus, it is not surprising that people ascribe mental states and capacities to AI, which is believed to mimic human intelligence and conduct both tedious and complex tasks.

Indeed, some previous studies employed mind perception theory to investigate how people perceive AI-enabled automated agents and their products or services. The first group of researchers focused on the uncanny valley of humanoid robots and attempted to discover the cause of uncanny valley perception. Gray and Wegner (2012) found that mind perceptions of experience elicit feelings of unease and uncanniness from humanlike robots, machines, and people lacking mental capacity. Appel et al. (2020) also found that mind perception of experience from a robot yields stronger feelings of eeriness than mind perception of agency, which yields more eeriness than a robot without a mind. The common findings proved that experience perception of humanoid robots has a huge impact on perceived uncanniness.

AI-enabled service agents and their services are the areas where mind perception theory is relatively often used in research. The general findings support the evidence for the advantages of perceiving mental states from virtual service agents. For example, in the context of customer service, Lee et al. (2020) found that the more people perceive a mind behind a chatbot, the more co-presence and interpersonal closeness they experience with the chatbot, and thus are more willing to use the chatbot. However, the authors used one combined factor of mind perception rather than examining the roles of agency and

experience perceptions separately. Söderlund and Oikarinen (2021) confirmed that attributions of agency, emotionality, and morality to virtual agents in frontline customer services enhance perceived humanness, which is positively related to customer satisfaction. Focusing on medical services, Wu et al. (2021) found that patients perceive higher experience and agency from human physicians than AI, which explains why patients are less receptive to AI than human physicians.

Some researchers also demonstrated that the mind perception of AI-enabled service agents is helpful in service failure situations. Yam et al. (2021) found that high levels of perceived experience, but not agency, attenuate the negative impacts of service failures on customer satisfaction. In contrast to Yam et al.'s (2021) findings, Srinivasan and Sarial-Abi (2021) confirmed the effect of agency perception. Their findings showed that consumers respond less negatively to algorithm-caused errors (vs. human-caused errors) because consumers perceive a lower mind perception of agency from an algorithm than humans, which lowers perceptions of the algorithm's responsibility. In sum, mind perception of AI service agents is beneficial to drawing positive consumer responses, and the effect is found to be both from agency and experience perceptions. However, the contrasting findings of Yam et al. (2021) and Srinivasan and Sarial-Abi (2021) indicate that agency and experience perceptions may affect differently depending on the contexts.

One study investigated people's perception of AI agents working to create art from the view of mind perception theory. Lima et al. (2021) asked participants to evaluate the algorithms' ability to create art (i.e., art agency) and experience art (i.e., art experience), as well as general experience and agency perception. Their results showed that participants attributed moderate levels of art agency (M=2.59 on a 5-point scale) and

low art experience (M=1.10 on a 5-point scale) to algorithms. Also, the main finding was that assessing an AI's lack of mind could impact how people subsequently evaluate AI-generated art. Although Lima et al. (2021) did not compare mind perception of algorithms to human designers, their findings provide an initial insight into mind perception of AI generating creative work.

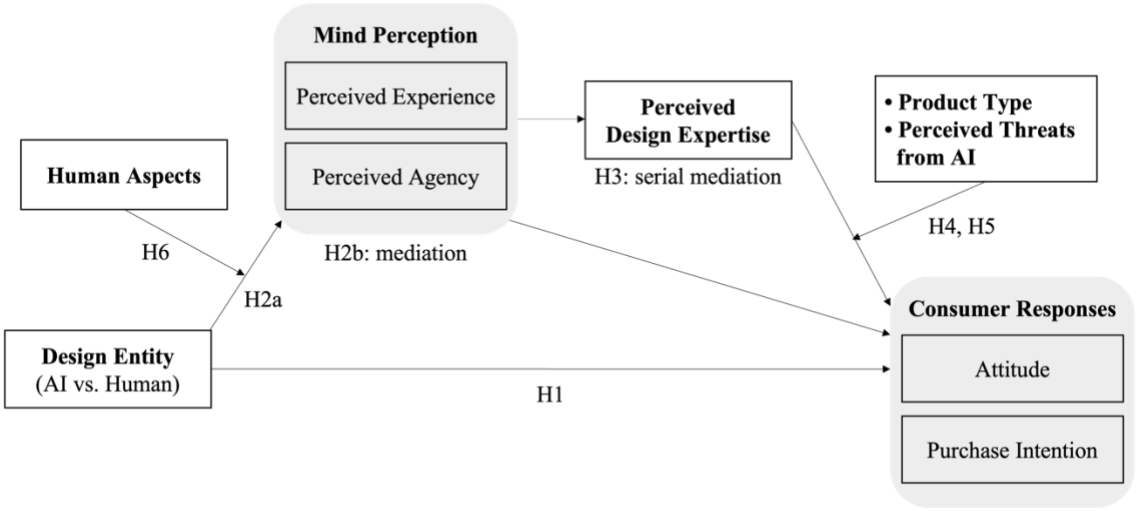
Furthermore, a few recent studies investigated the boundary conditions that change the effects of mind perception of AI-enabled service agents on consumer responses. Srinivasan and Sarial-Abi (2021) proved the moderating roles of algorithm characteristics (i.e., whether the algorithm is anthropomorphized, whether it involves machine learning) and task characteristics (i.e., whether the task is subjective or objective, whether it is interactive or noninteractive) in AI-led service failure contexts. Similarly, Xie et al. (2022) found the moderating role of product type. Their findings showed that consumers tend to avoid algorithms less when search products are recommended than experience products, because consumers have a higher cognitive conflict when AI (vs. human) recommends experience products. These studies imply the need for further investigation of the conditions that can alter the effects of inferring mental states of AI agents on consumer evaluation of the agents and their work, which is one of this study's objectives.

2.3 Hypotheses Development and Research Model

In this section, the hypothesized research model shown in Figure 5 is presented. The development of each hypothesis is described in detail.

Figure 5

Hypothesized Model



2.3.1 Effect of Design Entity on Consumer Responses

Extensive studies have been carried out to investigate how people respond to AI's work in recent years. Studies show that people generally tend to be less receptive to the judgments made by AI than humans (e.g., Castelo et al., 2019; Dietvorst et al., 2015; Granulo et al., 2021). This phenomenon of avoiding AI's work is known as algorithm aversion, defined as the tendency of people to prefer human decisions to algorithm decisions and being reluctant to accept algorithm decisions (Dietvorst et al., 2015). Consumers show acceptance of AI's decisions and advice from AI in a few specific situations (algorithm appreciation; e.g., Longoni & Cian, 2022; Xie et al., 2022), such as in utilitarian-oriented or factual information search cases. However, the majority of the existing studies support the view that consumers are less receptive to AI compared to human work in most cases.

Then, what if consumers are given fashion products described to be designed by AI or human designers? The findings of the recent studies emphasize the importance of considering the situation-specific factors that may affect consumer preferences for works from AI versus humans. Three studies (Sohn et al., 2020; Xu & Mehta, 2022; Zhang et al., 2022) explored consumer responses to AI-designed fashion products. Focusing on willingness to pay, Sohn et al. (2020) found that the young generation is more willing to pay for GAN-generated (vs. non-GAN-generated) fashion products, and Zhang et al. (2022) found that Chinese consumers are willing to pay more for AI-designed products. Xu and Mehta (2022) provided more direct evidence for the superiority of human-designed fashion products in terms of consumer attitudes. Xu and Mehta (2022) confirmed that consumers form more negative brand attitudes when facing AI-designed (human-designed) products due to decreased perceived brand essence, and such effect is stronger for fashion products. Also, based on the literature on consumer responses to AI-generated creative works, this study posits that consumers will evaluate fashion products designed by human designers more favorably than by AI. As presented above (see 2.1.3 and Table 3), the mainstream findings on AI-generated creative works provide evidence for a negative bias toward AI works (Moffat & Kelly, 2006; Ragot et al., 2020; Xu & Mehta, 2022). Although a few studies found no significant difference between people's evaluation between AI-created and human-created works (Hong, 2018; Xu et al., 2020), empirical findings on consumers' preference for AI-generated works over human-generated works lack except for Lopez et al.'s (2019) study.

Furthermore, it is valid to expect consumer preference for human-designed fashion products over AI-designed ones considering the nature of the product design

process. Designing products has been considered a human-dominant area that accompanies designers' know-how, expertise, and intention (Fu et al., 2006; Lawson & Dorst, 2013). In order to develop strategies to convey intended meaning and value through the design elements with given budgets and information, designers' experiential and domain-specific knowledge across the stages of the design process is required (Lawson & Dorst, 2013; Popovic, 2004). In addition to functionality, a consideration of expected users' subjective needs and value creation is another essential part of product design (Zöller, 2019). Especially in the fashion industry, designers' roles and identities are prominent in representing the products and can serve as a proxy for the products (Bye, 2010; Fuchs et al., 2013).

A few empirical studies investigating consumer responses to AI's work can provide a cue to the connection between product design and AI (vs. human) as a design entity. Consumers are averse to accepting AI's work when the work is highly subjective (vs. highly objective) in nature because they believe algorithms are not capable of performing subjective tasks (Castelo et al., 2019). Also, compared to AI's work, human work is more appreciated for products with symbolic value or with value to express something about one's personality or beliefs (Granulo et al., 2021). Accordingly, it is hypothesized that consumers will evaluate products more favorably when the products are described to be designed by humans than AI.

H1. Consumers will show more favorable responses (positive attitude and purchase intention) toward fashion products described to be designed by humans than AI.

2.3.2 Mediation of Mind Perception and Perceived Design Expertise

If consumers' preferences for human-designed fashion products over AI-designed products hold true, why do people evaluate the two differently? Anchored on mind perception theory (Gray et al., 2007), this study posits that mind perception of design entity (AI vs. human) will explain consumer evaluation of the products designed by the entity. Mind perception theory suggests that people perceive high experience and high agency from adult humans, whereas people infer much low experience and moderately low agency from robots (See Figure 4). Mind perceptions of an entity can show slight differences depending on the context, such as culture (Takahashi et al., 2016) or characteristics of perceiver and perceived entity (Waytz et al., 2010). Still, a few existing studies on AI implies that AI agents are ascribed to lower experience and agency compared to human agents (Srinivasan & Sarial-Abi, 2021; Wu et al., 2021).

In line with the findings, this study expects consumers facing AI will show lower levels of mind perception of experience and agency than those facing human designers. Experience, the ability to subjectively feel and experience emotions, is an essential human trait that AI cannot imitate (Gray et al., 2007; Lin et al., 2022; Wu et al., 2021). The term *experience gap* well illustrates the lack of perceived experience from machines; it refers that humans are deemed to be significantly more capable of experiencing emotion and sensation than robots and other machines (Gray & Wegner, 2012). It is true that some advanced AI is considered to have the ability to carry out complex tasks that are not easy for humans to complete. Some may thus rebut that agency is a primary characteristic of advanced AI. However, people are unlikely to perceive higher intentional capacity from AI than humans for all factors in agency dimensions, such as

morality and communication. In other words, people will be inclined to infer lower abilities to AI than humans if they are asked the inferred degree to which an entity can tell right from wrong, try to do the right thing, and convey thoughts or feelings to others.

Furthermore, the different levels of mind perception of the design entity (AI vs. human) are likely to affect consumer evaluation of the designed product. Literature shows that the mind perception of an AI agent consequently explains how people respond to the products or services provided by the AI agent (e.g., Kim et al., 2022; Lee et al., 2019; Söderlund & Oikarinen, 2021; Waytz et al., 2014). For example, Wu et al. (2021) proved the mechanism of medial AI aversion from mind perception theory. Their findings confirmed that patients show reluctance to the same treatment plan proposed by AI than a human physician, because they infer lower experience and agency from AI than human physicians. This line of research indicates the consequent impact of mind perception on perceiver's evaluation of perceived entities' products.

Few studies explored the role of mind perception in the context of fashion. However, given that consumers infer designers' abilities in functional and experiential aspects (Fu et al., 2006; Lawson & Dorst, 2013; Lin & Chang, 2021), it is likely that consumers will ascribe certain levels of experience and agency to fashion designers and evaluate the designed products based on that mind perception. At the same time, fashion designers design products to perform the desired function, they are anticipated to draw emotional connection from the design thereby offering enhanced experiential and symbolic merits (Ardelet et al., 2015; Lamb & Kallal, 1992). Furthermore, in line with the literature on mind perception theory from various research areas, consumers will perceive lower experience and agency from AI designers than humans. Therefore, on the

basis of mind perception theory, the following hypotheses are formulated regarding the relationship between design entity and consumer responses to the designed product.

H2a. Consumers will infer lower experience and agency from AI than from human designers.

H2b. Mind perception of experience and agency will mediate the relationship between design entity and consumer responses.

According to mind perception theory, ascribing mental states is a pre-attributional process (Epley & Waytz, 2010). People infer one's mind along with the two dimensions (i.e., experience and agency) to identify causes that might explain or predict the entity's behavior (Epley & Waytz, 2010; Premack & Woodruff, 1978). This fundamental premise of the theory implies the need for investigating the third factor explaining the relationship between mind perception and perceiver's end responses. While mind perception of experience and agency describes how a perceiver forms specific responses to a perceived entity's work, examining a situation-specific mediator will enlighten why such an effect occurs. Indeed, a few researchers investigated the role of a second mediator between mind perception and the end responses (e.g., Söderlund, 2022; Yam et al., 2022). For example, in the context of delivering negative feedback on employee performance, Yam et al. (2022) found that anthropomorphism is positively associated with robot supervisor-directed retaliation through the serial mediating effects of perceived agency and perceptions of abuse.

In this study, it is important to further understand the psychological processes that lead to consumers' embrace of AI working for the product design process and their

products. Accordingly, this study proposes perceived design expertise as the underlying mechanism between mind perception of design entity (AI vs. human) and consumer evaluation of the designed product. Design expertise can be conceptualized as a set of learned skills and knowledge in design based on personal characteristics and the accumulation of experience (Cross, 2004; Lawson & Dorst, 2013). The design expertise of designers is relative rather than absolute, and it is something that distinguishes experts from novices in terms of the ability to respond to the varying environment and adapt actions accordingly (Cross et al., 1994; Lawson & Dorst, 2013). Playing the inherent and central role in achieving design success (Schreier et al., 2012), design expertise is considered a heuristic cue that affects persuasion (Ratneshwar & Chaiken, 1991).

When exploring the key features of design expertise, design studies have consistently emphasized both emotional and experiential ability and logical analysis as vital qualifications for expert designers (Lawson & Dorst, 2013). Successful product design is believed to lie in designers' ability to consider design functionality and strategically maximize the use of limited resources (Hollins & Pugh, 1990). At the same time, design elements are often deemed relative to emotional and subjective aspects; designers are expected to entail the ability to be sensitive to changes in consumer needs and trends and augment value from design (Bloch, 1995; Zöller, 2019). In sum, designers' acumen can be considered along with experiential and agentic capabilities. Furthermore, the fashion design process is deemed a unique area that needs specialties both in product functions, trends, emotional values, and symbolic meanings in the design elements (Lamb & Kallal, 1992; Lennon et al., 2017). For that reason, it is expected that

mind perception of experience and agency of the design entity will predict the perceived design expertise of the design entity.

The impact of perceived design expertise of designers on consumer evaluation of the product has been examined (e.g., Crilly et al., 2004; Hsieh, 2014; Ratneshwar & Chaiken, 1991). Especially for the design of tangible, symbolic products, such as fashion products, designers can be viewed as the message source who transmit intended meanings through the product (Crilly et al., 2004). The perception of or inference about the design source of fashion products can affect subsequent consumer evaluation of the products, including design quality perceptions, feelings, and product demand (Fuchs et al., 2013). Thus, the design expertise of the designer, which is an essential domain-specific ability in design, is expected to predict consumer evaluation of the products. Xu and Mehta (2022) recently provided the first indication of the perceived design expertise of AI. Their results showed that consumers perceive lower design expertise from AI than humans. However, their study focused on brand essence instead of design expertise, finding the insignificant role of design expertise in explaining consumer attitudes. Contrary to their findings, this study posits that perceived design expertise derived from mind perception is associated with consumer responses based on mind perception theory and the related literature. Accordingly, this study hypothesizes the serial mediation effect of mind perception (experience and agency) and perceived design expertise, explaining the effect of design entity and consumer evaluation.

H3. Mind perception of experience and agency and perceived design expertise will serially mediate the relationship between design entity and consumer responses.

2.3.3 Moderation of Product Type, Perceived Threat, and Human Aspects

Given that mind perception theory is expected to unveil why the effect of design entity on consumer responses holds, such effect will differ for self-expressive versus functional products. Self-expressive products denote the products that are used to express one's self-images and personality or convey personal tastes and beliefs (Aaker, 1997). Consumers may purchase products from a brand that aligns with their own lifestyle or status to signal their identity and tastes (Chan et al., 2012; Wan et al., 2018). On the other hand, functional products focus more on practical attributes to meet functional, practical, or cognitive-oriented utility. Functional products are considered essential or utilitarian tools for completing a practical task or achieving a goal (Dhar & Wertenbroch, 2000). Consumer researchers have long distinguished self-expressive from functional products because of distinct differences in various dimensions, such as product attributes, expected value, consumer preferences, evaluation, and shopping patterns (Aaker, 1997; Jin et al., 2018; Steinhart et al., 2014; Wan et al., 2018).

This study hypothesizes that consumers' negative responses to AI-designed (vs. human-designed) products may be weakened for functional products but strengthened for self-expressive products. First, the literature has examined the boundary conditions of consumers' receptivity to AI based on utilitarian versus hedonic contexts (e.g., Im & Lee, 2023; Longoni & Cian, 2022; Ruan & Mezei, 2022). Utilitarian products include those with practical or rational value whereas hedonic products involve those with emotional or sensory value (Babin et al., 1994; Hirschman & Holbrook, 1982). Although findings up to now generally support algorithm aversion, a few recent findings denote that consumers less negatively react against AI works in utilitarian contexts (e.g., Longoni & Cian,

2022). Longoni and Cian (2022) found that people perceive AI recommenders to be more competent for utilitarian tasks but less for hedonic tasks than humans. Nozawa et al. (2022) confirmed that consumers negatively evaluate food and restaurants when receiving services from AI (vs. humans). This negative effect of AI services was higher in luxury restaurants than in fast food or casual dining, which was explained from the perspective of hedonic and utilitarian consumption.

Although not the same, the past findings on hedonic versus utilitarian contexts can apply to self-expressive versus functional products to some extent. Compared to one another, functional products mainly center around practical and utilitarian properties while self-expressive products encompass lower functional properties (Baek et al., 2010). It is true that self-expressive products embrace both utilitarian values of meeting one's needs to maintain a self-identity and hedonic values of fulfilling emotional needs (see Morgan & Townsend, 2022 for details). However, compared to functional products, self-expressive products are more explicitly associated with hedonic values because they fulfill consumers' emotional needs and make consumption pleasure experience (Aaker, 1999; He et al., 2019; Millan & Reynolds, 2014; Rifkin et al., 2021) and correlate highly with hedonic values (Yoo & Park. 2016). Thus, one can suspect that consumers' less (vs. more) negative evaluation of utilitarian (vs. hedonic) AI works can provide a clue for less (vs. more) negative responses to AI-designed functional (vs. self-expressive) products.

Second, the moderating effect of self-expressive versus functional product type can be explained by mind perception theory. Experience gap, which explains the significant difference in perceived experience between machines and humans (Gray & Wegner, 2012), is likely to strengthen the negative responses to AI-designed self-

expressive products. Mind perception theory describes machines are perceived to have low experience but moderate agency (Gray et al., 2007). AI is even more associated with rational problem-solving and logical computational procedure due to its rule-based operation (Longoni & Cian, 2022; Nozawa et al., 2022; Ruan & Mezei, 2022), which may positively affect perceived agency but not experience. If the designed products are supposed to convey one's dispositional information or subjective opinion (self-expressive products), AI's low perceived mental capacity to experience affective and emotional feelings will explain the more negative evaluation of AI-designed self-expressive products. On the contrary, AI's moderate perceived intentional ability to act and plan will explain the less negative evaluation of AI-designed functional products.

A few studies have tested the role of mind perception in explaining the varying effects of AI on consumer responses depending on contexts (Castelo et al., 2019; Srinivasan & Sarial-Abi, 2021; Xie et al., 2022). Consumers tend to be less open-minded to AI for highly subjective tasks compared to objective tasks (Castelo et al., 2019; Srinivasan & Sarial-Abi, 2021). Similarly, consumers are more inclined to avoid recommendations from AI for experience products than search products (Xie et al., 2022). The authors explained such differences occur because AI is perceived to lack empathy or affective capability needed for subjective or experiential tasks. In this vein, the differences between self-expressive and functional products in terms of their relatively distinct attributes and inherent values (i.e., emotional or subjective vs. functional or objective) suggest the moderating effect of product type. The effect of design entity on consumer responses will be weakened (vs. strengthened) for functional (vs. self-expressive) products. Furthermore, the effect of perceived experience and

agency of AI versus human designers on consequent product evaluations will be differentially affected by whether the product is self-expressive or functional.

H4a. Consumers' negative responses to AI-designed fashion products will be weakened (vs. strengthened) for functional (vs. self-expressive) products.

H4b. The mediating effect of perceived agency (vs. experience) on the relationship between design entity and consumer responses will be strengthened for functional (vs. self-expressive) products.

Next, consumers' perceived threat from AI is proposed as a critical consumer characteristic that will moderate the effect of design entity on consumer responses through mind perception. Perceived threats from AI are conceptualized as the extent to which consumers perceive AI to be intimidating or threatening because of its novelty and hyper-automation (van Esch et al., 2021b). The information system (IS) literature has long reported that people feel threatened by novel technology when they are uncomfortable and distressed with the technology or the potential usage of the technology is seen to change their norms (Khasawneh, 2018; Rosen & Weil, 1995). Technology-related fears are also referred to as technophobia, which induces unpleasant feelings of fear and intensifies the avoidance of technology due to the attribution of negative traits to technology (Mason et al., 2014; Oh et al., 2017).

AI is expeditiously becoming more pervasive, easier to adopt in daily lives, and able to perform routine tasks mostly done by humans with automatization and prediction. These characteristics of AI distinguish AI from other technologies in that AI is tacitly perceived as more human-like, even though people differentiate AI from humans by

calling AI an “other” (Oh et al., 2017). Fear or threats from AI encompasses the fear of algorithmic surveillance and privacy concerns (Mason et al., 2014; Segijn et al., 2022), job insecurity and mass unemployment (Blanas et al., 2019; Yam et al., 2023), economic concerns (Kirkpatrick et al., 2022), and concerns for fake output and lack of trust (Missaoui et al., 2019).

In this vein, the effect of design entity on consumer responses is expected to be weakened (vs. strengthened) for consumers with lower (vs. higher) threats from AI. Furthermore, suppose mind perception of experience and agency explains why consumers act more negatively against AI-designed fashion products than human-designed ones. In that case, such effect will be stronger for consumers who feel more threatened by AI. This study proposed perceived design expertise as a second serial mediator that explains the effect of mind perception on consumer responses. Because perceived threats from AI is characterized by intensified AI avoidance and the fearful concerns that AI would replace human jobs with improved ability (Haenlein & Kaplan, 2019; Pan & Froese, 2023; Yam et al., 2023), the effect of perceived design expertise on the evaluations of AI-designed versus human-designed products is likely affected by perceived threats from AI. Consequently, the effect of design entity on consumer evaluations through mind perception will be amplified (reduced) for those with higher (lower) perceived threats from AI. Mind perception will more strongly explain why consumers prefer human-designed fashion products to AI-designed ones if they perceive higher AI threats. On the other hand, the differences in the evaluations of AI-designed and human-designed products due to mind perception will be weakened for consumers with lower perceived threats from AI. In sum, the mediating effects of perceived

experience and agency on consequent product evaluations will be positively moderated by the extent to which consumers are threatened by AI.

H5a. Consumers' negative responses to AI-designed fashion products will be weakened (vs. strengthened) for those who perceive lower (vs. higher) threats from AI.

H5b. The mediating effect of perceived experience and agency on the relationship between design entity and consumer responses will be weakened (vs. strengthened) for those who perceive lower (vs. higher) threats from AI.

Lastly, drawing upon mind perception theory, this study proposes the moderating role of human aspects in AI-assisted design process on the effects of the design entity on consumer responses. The idea of machines collaborating with humans to increase work performance is not new. As Colgate et al. (1996) specified, since the birth of machines and robots, the ultimate goal has been to make them assist humans. Furthermore, the recent advance in AI expedited researchers' curiosity about how human-AI collaboration can be applied to various technology-mediated settings. Collaborative intelligence, proposed by Epstein (2015), conceptualizes the practice that humans assign specific tasks to AI to share tasks with them. The predominant view around collaborative intelligence is that AI and humans may enhance each other's complementary strengths rather than a substitute for one another (Wilson & Daugherty, 2018). For example, researchers suggest humans are mainly responsible for feeling and experiential activities, and machines such as AI are mainly responsible for cognitive activities (Rust & Huang, 2021). Empirical findings imply the effectiveness of joint forces of AI and humans in many retail realms,

including market positioning strategy (Huang & Rust, 2022), frontline customer service (Noble et al., 2022; Peng et al., 2022), employee training (Luo et al., 2021), and logistics management (Loske & Klumpp, 2021).

Some design studies suggested that hybrid human-AI collective intelligence in the product design stage predicts some advantages such as improving efficiency (Figoli et al., 2022; Liao et al., 2020; Verganti et al., 2020). Then, how does the human-AI collaboration in the fashion design process affect consumers' perception? This study hypothesizes that the extent to which human aspects are incorporated into AI applications will moderate the relationship between design entity and consumer responses, since a high human aspect will attenuate the negative effects of AI on mind perception. As discussed in the mind perception theory literature and hypothesized above, consumers are likely to perceive significantly more experiential and agentic capabilities from humans than from AI (Lee et al., 2019; Waytz et al., 2014). Suppose mind perception explains the relationship between design entity (AI vs. human) and consumer evaluation of the designed fashion products. The intervention of human components in the AI design process will attenuate consumers' negative responses toward products described to be designed by AI. In other words, adding human aspects to the AI applications in the design process will help improve the decreased mind perception of experience and agency of AI, consequently weakening the negative effect of AI as a design entity.

This study operationalizes the level of human aspects in the AI-assisted design process as three levels: AI (low), humanized AI designer (moderate), and human-AI collaboration (high). Humanized AI designer represents the brand's message embracing human-likeness of AI technology in the product design process. Humanizing or

anthropomorphizing AI is one of the major topics of discussion in industry and research (e.g., Ahn et al., 2021; Fenwick & Molnar, 2022; Mellers et al., 2023). The industry is employing humanized AI agent as one of the tactics to promote and reposition their AI technology beyond calculation, automation, and number-crunching (Banerjee, 2021). While researchers are still actively clarifying the conceptualization of humanizing (Fenwick & Molnar, 2022), it has been found to reduce people's resistance to AI (Mellers et al., 2023) or even increase positive behavioral intention (Bakpayev et al., 2022; Hong et al., 2022), which can be explained by enhanced perceived similarity (Ahn et al., 2021; David-Ignatieff et al., 2023) and trust (Huh, Whang, and Kim, 2023; Waytz et al., 2014). Chamberlain et al. (2018) suggested that people's prejudices against computer-generated artwork can be lessened when people infer anthropomorphic characteristics in computer programs. Waytz et al. (2014) confirmed the benefit of humanizing technology under mind perception theory, finding that consumers tend to trust anthropomorphized technology would perform its task well.

Human-AI collaboration represents having the highest level of human aspects in AI applications because human work is the most involved. While several recent studies in retail highlighted the benefits of human-AI collaboration, Srinivasan and Sarial-Abi's (2021) findings can especially support the current study's view using mind perception theory. Srinivasan and Sarial-Abi (2021) showed that consumers respond less negatively to algorithm error than human error. Furthermore, the findings proved that consumer responses to a brand harm crisis caused by an algorithm error are more negative when there is human supervision after the harm crisis. In contrast, consumers' responses are less negative when there is technological supervision of the algorithm following the harm

crisis. Srinivasan and Sarial-Abi's (2021) findings indicate the opposite impact of algorithms because they focused on error scenarios (vs. product design scenarios in the current study). However, the reasoning that human intervention will help enhance the decreased mind perception of an algorithm is consistent with the current study. Therefore, this study hypothesizes the moderating effect of an intervention of humans in the AI design process on the relationship between design entity and consumer responses.

H6. The effect of design entity on consumer responses through mind perception will be moderated by the level of incorporating human aspects into AI applications. That is, consumers' negative responses to AI-designed fashion products will be weakest when the products are described to be designed through human-AI collaboration, followed by Humanized AI designer and AI.

The hypothesized model depicting H1-H6 are shown in Figure 5.

Chapter 3. Overview of Research Methods and Pilot Study

Chapter 3 describes the overview of the research methods and the description of the pilot study conducted before collecting the data for the main studies (i.e., Study 1 and Study 2). After the hypotheses are restated, the overview describes the methodological approach of the study. Next, the descriptions of the pilot study and its findings and discussion are presented.

H1. Consumers will show more favorable responses (positive attitude and purchase intention) toward fashion products described to be designed by humans than AI.

H2a. Consumers will infer lower experience and agency from AI than from human designers.

H2b. Mind perception of experience and agency will mediate the relationship between design entity and consumer responses.

H3. Mind perception of experience and agency and perceived design expertise will serially mediate the relationship between design entity and consumer responses.

H4a. Consumers' negative responses to AI-designed fashion products will be weakened (vs. strengthened) for functional (vs. self-expressive) products.

H4b. The mediating effect of perceived agency (vs. experience) on the relationship between design entity and consumer responses will be strengthened for functional (vs. self-expressive) products.

H5a. Consumers' negative responses to AI-designed fashion products will be weakened (vs. strengthened) for those who perceive lower (vs. higher) threats from AI.

H5b. The mediating effect of perceived experience and agency on the relationship between design entity and consumer responses will be weakened (vs. strengthened) for those who perceive lower (vs. higher) threats from AI.

H6. The effect of design entity on consumer responses through mind perception will be moderated by the level of incorporating human aspects into AI applications. That is, consumers' negative responses to AI-designed fashion products will be weakest when the products are described to be designed through human-AI collaboration, followed by Humanized AI designer and AI.

3.1 Overview of Research Methods

This study used quantitative methodology and online experiments were conducted for three reasons. First, quantitative research methodology allows researchers to test theory-driven hypotheses based on numerical data, efficient data analysis, and statistical evidence on relationships between interested variables (Black, 1999; Creswell, 2014). Under the framework of mind perception theory, this study aims to investigate the relationships between the following variables: design entity, mind perception, perceived design expertise, consumer responses, product type, perceived threats from AI, and human aspects in AI applications. Thus, the objective of the study aligns with the use of quantitative methodology.

Second, the purpose of an experiment is to test hypotheses about causal relationships between variables. Leveraging experimental design, researchers can manipulate independent variables, utilize randomization, and thus systematically examine whether the hypothesized causal effect of the predictors on the outcome variables of interest hold true (Kirk, 2012; Shadish et al., 2002). Experimental design is appropriate for the study objective, as it helps answer whether or not design entity (AI vs. human) causes different outcomes in terms of mind perception, perceived design expertise, and consumer responses. Furthermore, manipulating product type or human aspects in AI applications while holding other variables constant sheds light on the understanding of the boundary conditions hypothesized based on mind perception theory and the relevant literature.

Third, online experiments using an online survey platform, such as Amazon Mturk or Prolific, can be regarded as a widely accepted approach in the consumer research area (Bleier & Eisenbeiss, 2015). Online experiments can effectively ensure random sampling, which helps achieve the external validity of the research. Participants recruited from online participant recruitment platforms well represent the overall U.S. population (Difallah et al., 2018; Kees et al., 2017) and generate good quality data when techniques to detect careless or inattentive responses are employed (Curran, 2016; Peer et al., 2017; Ratcliff & Hendrickson, 2021). The sample representativeness ensures the generalizability of the study findings to the population, and thus, help increase the external validity of the study. Furthermore, the use of online platforms for administering a questionnaire and participant recruitment has many advantages, such as easy subject

pool access, relatively low cost, and faster iteration between theory development and experiment (Hulland & Miller, 2018).

A total of three studies was conducted to test the hypothesized model: a pilot study, Study 1, and Study 2. A pilot study was conducted before designing the main studies for two purposes. The first purpose of the pilot study was to test H1 which hypothesized the effect of design entity (AI vs. human) on consumer responses (i.e., product attitude, purchase intention) and the mediating effect of design expertise explaining such effect. Second, the pilot study aimed to provide an insight into how to develop the study designs of the main studies.

Next, Study 1 and Study 2 were conducted as the main experimental studies for testing the hypotheses. Three pretests were conducted before the main studies. The purposes of the pretests were to select the appropriate product image stimuli and fictitious brand name (Pretests 1 & 2) and to check whether the study scenarios (Pretest 2) or advertisement stimuli (Pretest 3) manipulate design entity, product type, or design process well. Study 1 aimed to test the main effect of design entity on consumer responses (H1) and mind perception (H2a), the mediation effect of mind perception (H2b), and the serial mediation effects of mind perception and perceived design expertise in the relationship between design entity and consumer responses (H3). Also, Study 1 tested the moderating effect of product type (H4) and perceived threats from AI (H5). Study 2 examined whether human aspects in AI applications moderate the relationship between design entity and consumer responses (H6).

3.2 Pilot Study

The purpose of the pilot study was to provide preliminary evidence of H1, which predicts that consumers will show more favorable responses to the product designed by human designers than by AI. Also, the role of perceived design entity in mediating the effect of design entity on consumer responses was tested in the pilot study. Lastly, the pilot study aimed to offer insights into developing the main study design.

3.2.1 Study Design and Participants

A 2 (design entity: AI vs. human) × 2 (brand replicates) between-subject scenario-based experiment was conducted. Based on the previous literature (e.g., Lee et al., 2015; Ward & Dahl, 2014), Louis Vuitton and H&M were used to represent different brand types with different brand statuses and reputations. Design entity and brand replicates were manipulated using online shopping scenarios. A sweater was used as the apparel product in the scenarios because past studies found that the conceptualization of sweaters is relatively well-defined, consistent among people, and stable over time (DeLong et al., 1986). One hundred and forty-two adults living in the U.S. were recruited through an online participant recruitment website, Amazon Mechanical Turk (Mturk). Twenty-one participants were eliminated because (a) they indicated disqualification from participating in the study or (b) they failed the involvement check questions. The final sample for further analysis was 121 participants (M_{age}=38.84, SD_{age}=11.59). Table 4 presents the participant characteristics.

Table 4

Participant Characteristics (Pilot Study)

Characteristics		**N**	**Percent**
Gender	Male	81	66.94%
	Female	39	32.23%
	Other; prefer not to answer	1	0.83%
Ethnicity	White / Caucasian	90	74.38%
	Hispanic or Latino	13	10.74%
	Asian	10	8.26%
	Black, African, African American	6	4.96%
	Other	2	1.65%
Income	Less than $25,000	19	15.70%
	$25,000 - $49,999	43	35.54%
	$50,000 - $74,999	28	23.14%
	$75,000 - $99,999	23	19.01%
	$100,000 or more	8	6.61%
Education *(highest degree received)*	High school or equivalent (e.g., GED)	12	9.92%
	Some college, but no degree	14	11.57%
	Associate's degree	10	8.26%
	Bachelor's degree	60	49.59%
	Master's degree	22	18.18%
	Professional degree	2	1.65%
	Doctoral degree	1	0.83%
Marital status	Married	68	56.20%
	Single	44	36.36%
	Divorced	4	3.31%
	Separated	1	0.83%
	Widowed	3	2.48%
	Other; prefer not to answer	1	0.83%
Total			**121**

3.2.2 Procedure

Once participants click the survey link on Amazon Mturk, they were given a consent form approved by the Institutional Review Board (IRB) at the University of Minnesota. After they signed the consent form and answered the qualification questions (i.e., living in the U.S., 18 years old or older), they were randomly assigned to one of the four conditions. Next, participants were asked to read a given shopping scenario and

completed the questionnaire by answering questions and providing demographic information. The shopping scenarios used in the pilot study were as follows:

> **AI condition:**
> *Imagine that you are looking for a special sweater for yourself online while navigating a fashion brand's website. You found the item you have always wanted from the fashion brand (Louis Vuitton vs. H&M). The sweater is designed by Artificial Intelligence (AI). AI algorithm used by (Louis Vuitton vs. H&M) analyzed the trends and images to learn about styles of (Louis Vuitton vs. H&M) and created the new item. A consumer report had assessed the sweater to be fashionable and in line with (Louis Vuitton vs. H&M)'s values, style, and personality.*
>
> **Human condition:**
> *Imagine that you are looking for a special sweater for yourself online while navigating a fashion brand's website. You found the item you have always wanted from the fashion brand (Louis Vuitton vs. H&M). The sweater is designed by the brand designers. Professional designers in (Louis Vuitton vs. H&M) analyzed the trends and the styles of (Louis Vuitton vs. H&M) clothing and created the new item. A consumer report had assessed the sweater to be fashionable and in line with (Louis Vuitton vs. H&M)'s values, style, and personality.*

3.2.3 Measurements

All measurement items were drawn from past studies and modified to fit the study context. Product attitude (α=.94; Chae & Hoegg, 2013) was measured using three 7-point semantic scales: *negative – positive*, *dislikable – likable,* and *bad – good.* Purchase intention (α=.95; Dodds et al., 1991) was measured using four items, *The likelihood of purchasing this sweater is high*, *I would consider buying the sweater*, *The probability that I would consider buying the sweater is high*, and *My willingness to buy the sweater is high*, employing 7-point Likert scales (1=*Strongly disagree* – 7=*Strongly agree*). Perceived design expertise was measured through two items (Ratneshwar & Chaiken, 1991; Schreier et al., 2012) of 7-point semantic scales: "In your opinion, how high is the

design expertise of the (designers vs. AI) for the brand in the scenario?" *They have very low design expertise – They have very high design expertise* and "Do you think that the (designers vs. AI) designing for the brand in the scenario have the necessary skills / know-how to design new products?" *They don't have the necessary skills – They have the necessary skills*. Because the pilot study used real brands, brand attitude, brand luxuriousness, and brand reputation were also measured using single 7-point semantic scale items: *negative – positive*, *mainstream – luxury*, and *bad reputation – good reputation.*

3.2.4 Results

Participants perceived Louis Vuitton as more luxurious (M=6.52 vs. 4.34; $t(75)=7.07$, $p<.001$) and of a higher reputation (M=6.23 vs. 5.61; $t(119)=2.95$, $p=.004$) than H&M. However, brand attitude did not significantly differ between Louis Vuitton and H&M ($p=.130$). Thus, the two brands well represented different brand types with similar levels of brand attitude.

MANCOVA was first performed with brand attitude as a covariate. The multivariate results showed the significant main effect of design entity (Pillai's V=.09, $p=.013$, partial $\eta^2=.09$). Next, the results of ANCOVA with brand attitude as a covariate was used to test H1. As expected, participants in the human condition showed a more favorable product attitude (M_{AI}=5.72 vs. M_{human}=6.17; $F(1, 116)=5.19$, $p=.025$, partial $\eta^2=.04$) and marginally higher purchase intention (M_{AI}=5.17 vs. M_{human}=5.67; $F(1, 116)=3.67$, $p=.058$, partial $\eta^2=.03$) than those in the AI condition. Human designers were perceived to have higher design expertise than AI (M_{AI}=5.41 vs. M_{human}=6.10; $F(1, 116)=11.19$, $p=.001$, partial $\eta^2=.09$). The effect of brand on purchase intention was

significant (M_{LV}=5.16 vs. M_{HM}=5.68; $F(1, 116)=4.01$, $p=.047$, partial $\eta^2=.03$), whereas brand did not affect product attitude ($p=.351$). The effect of the interaction of design entity and brand type was not significant on product attitude and purchase intention.

PROCESS Model 4 (Hayes, 2017) with 5,000 bootstrap samples was performed to test the mediation of design expertise between design entity and product attitude and purchase intention. Brand attitude was entered as a covariate. The results confirmed the indirect effect of design entity through perceived design expertise on both product attitude (indirect effect: 0.42, 95% CI = [0.1699, 0.7266]) and purchase intention (indirect effect: 0.55, 95% CI = [0.2398, 0.9215]).

3.2.5 Discussion

The pilot study tested H1 of the study. The findings provided initial evidence that consumer show more favorable responses toward the products described as being designed by humans than AI (H1). In addition, the pilot study confirmed that perceived design expertise of AI versus human designers explains the effect. Participants perceived higher design expertise from humans than AI, and consequently, formed a more favorable attitude toward the product designed by humans than AI.

One thing to note is that the results on the effect of design entity on purchase intention showed weak evidence ($p=.058$). The results can be attributed to two possible explanations. First, it is possible that although consumers prefer human-designed products over AI-designed products, the effect of design entity on purchase intention is not extremely strong. This non-significant difference in purchase intention may be because the two brands (Louis Vuitton vs. H&M) represent the two extremes of luxury and fast-fashion brands. It is possible that the two extremes did not capture middle-

income consumers who were not highly willing to purchase either brand type (Das et al., 2022; Lo & Yeung, 2020), which may lessen the effect of design entity in the pilot study. Still, given the marginal significance level, it is worthwhile to reexamine the effect of design entity on purchase intention in the main studies. Second, given that brand type affected purchase intention (p=.047) but not product attitude (p=.351) in the pilot study, the results can be interpreted that existing brands yielded confounding effects (Schneider & Cornwell, 2005), thus impacting the findings on purchase intention. The use of existing brands in the pilot study helped develop realistic scenarios (Geuens & De Pelsmacker, 2017) and allowed confirming that the effect of design entity on consumer responses holds across different brand types. However, fictitious brands were used in subsequent main studies to thoroughly test the effect of design entity and avoid potentially confounding effects of existing brands (Geuens & De Pelsmacker, 2017).

Chapter 4. Study 1

Chapter 4 presents the Study 1 methods, results, and discussion. After the study design, procedure, and measurement are described in the methods section, preliminary data analysis and hypothesis testing is presented in the results section. The findings of Study 1 are discussed at the end.

4.1 Methods

The objectives of Study 1 were threefold. First, Study 1 tested whether AI and human as design entity affect consumer responses (H1) and mind perception (H2a) differently. Second, Study 1 tested the indirect effect of design entity on consumer responses through mind perception (H2b) and through mind perception and perceived design expertise (H3). Third, Study 1 examined the moderating effects of product type (self-expressive vs. functional) and consumers' perceived threats from AI on the relationship between design entity and consumer responses (H4, H5).

4.1.1 Study Design and Participants

A 2 (design entity: AI vs. human) × 2 (product type: self-expressive vs. functional) scenario-based between-subject experiment was conducted online. Design entity and product type were manipulated using hypothetical shopping scenarios. The number of participants for recruitment was determined based on an a priori power analysis using G*Power 3.1 (Faul et al., 2009) and the literature on the sample size. The power analysis showed that at least a sample size of 218 is needed for MANOVA to detect the effect size Cohen's f^2 of .02 with α of .05 and a power of .80 (Cohen, 1992). The effect size was computed using the pilot study's Pillai's trace (V=.09) and the

number of potential predictors (2 independent variables and 3 covariates) and response variables (6 dependent variables). Next, the literature on sample size was reviewed to see the suggestions on the relationship between the number of mediators and sample size. At least a sample size of 160 is suggested for a medium effect size with two mediators in the model (Sim et al., 2022). Thus, 300 adults living in the U.S. and fluent in English were recruited through Prolific to ensure an adequate sample size after potential careless response detection and data cleaning. Prolific Academic is an online participant recruitment platform that is widely used in consumer behavior research, since Prolific participants are known to be naïve, attentive, and less dishonest and thus provide high-quality data compared to other platforms (Eyal et al., 2022; Peer et al., 2017). Those who participated in Pretest 2 on Prolific were excluded from the study (see 4.1.2 for details of Pretest 2).

Multiple attention check questions (e.g., This is attention check. Please check '*Not at all*,' Through the scenario, you imagined that you saw a fashion product from a brand. What was the brand name?) were included to eliminate careless responses and ensure quality data (Curran, 2016). Eleven participants were excluded because they failed more than one attention check question, leaving 289 participants for the final sample (M_{age}=39.37, SD_{age}=15.06). Table 5 shows Study 1 participant characteristics.

Table 5

Participant Characteristics (Study 1)

Characteristics		**N**	**Percent**
Gender	Male	145	50.17%
	Female	139	48.10%
	Other; prefer not to answer	5	1.73%

Ethnicity	Middle Eastern and North African	2	0.69%
	Native Hawaiian or other Pacific Islander	2	0.69%
	White / Caucasian	207	71.63%
	Hispanic or Latino	32	11.07%
	Asian	13	4.50%
	Black, African, African American	26	9.00%
	Other	6	2.08%
Income	Less than $25,000	83	28.72%
	$25,000 - $49,999	84	29.07%
	$50,000 - $74,999	54	18.69%
	$75,000 - $99,999	28	9.69%
	$100,000 or more	38	13.15%
Education *(highest degree received)*	High school or equivalent (e.g., GED)	51	17.65%
	Some college, but no degree	71	24.57%
	Associate's degree	32	11.07%
	Bachelor's degree	102	35.29%
	Master's degree	28	9.69%
	Professional degree	5	1.73%
Marital status	Married	100	34.60%
	Single	144	49.83%
	Divorced	29	10.03%
	Separated	2	0.69%
	Widowed	6	2.08%
	Other; prefer not to answer	8	2.77%
Job situation	Full-time	118	40.83%
	Part-time	59	20.42%
	Unemployed	68	23.53%
	Retired	24	8.30%
	Other; Prefer not to answer	19	6.57%
Total			**289**

4.1.2 Pretests and Stimuli

Hypothetical shopping scenarios were developed to manipulate design entity and product type. The scenarios asked participants to imagine browsing online and seeing a jacket from a fictitious fashion brand Knizzaz's website. The design entity information (AI vs. human) and product type (self-expressive vs. functional) in the scenarios differed based on the study conditions. Following the suggestion from the existing literature that

compared human versus AI agent, the scenarios included brief descriptions of how the designs were made by either AI powered by data and algorithms or professional human designers with expertise (e.g., Hong, 2018; Zhang et al., 2022). A jacket was used as the product category in the scenarios across the conditions because jackets can have varying levels of self-expressive values (Chernev et al., 2011) and are sold across genders (Achabou et al., 2020). Following the descriptions of self-expressive and functional products in the literature, *a fashionable jacket* and *an insulated jacket* with additional descriptions were used in the scenarios to manipulate product types. The fictitious brand name and other information such as price and the new arrival were included identically across the conditions. This approach was adopted to ensure external validity by avoiding Hawthorne and John Henry effects, where participants detect the existence of study intervention and modify their survey responses (Adair, 1984), and minimize potential confounding effects.

Two pretests (Pretest 1 and Pretest 2) were conducted to ensure appropriateness of the scenarios. Pretest 1 (n=72; M_{age}=33.75, SD_{age}=10.38; Amazon Mturk) aimed to select the most appropriate fictitious brand name that would be used in the scenarios. Pretest 1 participants were given multiple fictitious brand names and indicated their opinions about each brand name. Brand familiarity and brand attitude were measured using single 7-point semantic scale items: *extremely unfamiliar – extremely familiar* and *extremely negative – extremely positive.* The brand name *Knizzaz* was selected because it had relatively neutral brand familiarity (M=4.28, SD=2.01) and brand attitude (M=4.67, SD=1.37) and was considered neutral in terms of self-expressive versus functional values compared to other brand names.

Pretest 2 (n=99; M_{age}=35.46, SD_{age}=12.14; Prolific) had two objectives: (a) to check successful manipulation of Study 1 scenarios and (b) to develop appropriate stimuli for Study 2 (see 5.1.2 for details of Study 2 part). For Study 1, Pretest 2 aimed to test if the study scenarios would successfully manipulate design entity (AI vs. human) and product types (self-expressive vs. functional). Pretest 2 had four study conditions, and each represented the actual study conditions with the scenarios: AI-designed self-expressive product, AI-designed functional product, human-designed self-expressive product, and human-designed functional product. Pretest 2 participants were randomly given one of four scenarios and indicated their opinions about the scenario.

The manipulation of design entity was checked with a single 7-point semantic scale item (Choi et al., 2021): "Through the scenario, you imagined that you saw a fashion product. Please indicate the extent to which the entity who designed the product was more like a computer system or a person." *Very machine-like, more like a computer system – Very human-like, more like a person.* Next, the manipulation of product type was checked using two scales. First, a single 7-point semantic scale item was used (Baltas et al., 2017): "In my opinion, the fashionable jacket is..." *Highly self-expressive – Highly functional.* The descriptions of self-expressive and functional attributes were given to participants based on the suggestion of the original source (Baltas et al., 2017; see Appendix A for full descriptions). Second, a four-item 7-point Likert scales (1=*Strongly disagree* – 7=*Strongly agree*) measuring product's signaling capability was used (α=.92; Wang & Wallendorf, 2006): *The jacket can convey one's personality to the people around him/her, reflect the owner's identity, shape the owner's image in the eyes of others,* and *tell others what kind of person the owner is.* The higher (vs. lower) the

average score of signaling capability, the more a product is perceived to be a self-expressive (vs. functional) product (Wang & Wallendorf, 2006).

The results of Pretest 2 showed successful manipulation of design entity and product type, indicating the appropriateness of the scenarios for Study 1. Design entity in the AI condition was perceived as less human-like (i.e., more machine-like) than the human condition (M_{AI}=2.14 vs. M_{human}=5.69; $t(98)$=-12.96, p<.001). Compared to an insulated jacket, a fashionable jacket was perceived to have more self-expressive (i.e., less functional) attributes ($M_{fashionable}$=2.83 vs. $M_{insulated}$=5.55; $F(1, 98)$=96.00, p<.001) and to be capable of signaling one's identity ($M_{fashionable}$=5.28 vs. $M_{insulated}$=4.00; $F(1, 98)$=38.36, p<.001). Thus, the scenarios were used in Study 1. The shopping scenarios used in Study 1 were as follows:

> **AI-designed self-expressive product condition:**
> *Imagine that you are navigating the internet to find a fashionable jacket. You think it is important to find a jacket that reflects your self-image. When you click on the website of KNIZZAZ, you see exactly what you want in the brand's new arrival collection. While reading the product description, you learn that the jacket was designed by algorithm-based Artificial Intelligence (AI). You feel the jacket is reasonably priced.*
>
> **AI-designed functional product condition:**
> *Imagine that you are navigating the internet to find an insulated jacket. You think it is important to find a jacket that guarantees high performance. When you click on the website of KNIZZAZ, you see exactly what you need in the brand's new arrival collection. While reading the product description, you learn that the jacket was designed by algorithm-based Artificial Intelligence (AI). You feel the jacket is reasonably priced.*
>
> **Human-designed self-expressive product condition:**
> *Imagine that you are navigating the internet to find a fashionable jacket. You think it is important to find a jacket that reflects your self-image. When you click on the website of KNIZZAZ, you see exactly what you want in the brand's new*

arrival collection. While reading the product description, you learn that the jacket was designed by an award-winning designer. You feel the jacket is reasonably priced.

Human-designed functional product condition:
Imagine that you are navigating the internet to find an insulated jacket. You think it is important to find a jacket that guarantees high performance. When you click on the website of KNIZZAZ, you see exactly what you need in the brand's new arrival collection. While reading the product description, you learn that the jacket was designed by an award-winning designer. You feel the jacket is reasonably priced.

4.1.3 Procedure

Once participants clicked the survey link on Prolific, they read an IRB-approved consent form. After they agreed to participate in the study and answered the qualification questions (i.e., living in the U.S., 18 years old or older), they were randomly assigned to one of the four conditions. Participants read a hypothetical shopping scenario (see 4.1.2), imagined seeing a jacket online, and completed the questionnaire by answering questions. The questionnaire showed the manipulation check questions, the questions measuring the variables about design entity, product, brand, and covariates, and attention check questions. Participants provided demographic information at the end of the questionnaire. Each participant received $1.60 as an incentive upon completion.

4.1.4 Measurements

All measurements were adopted from the existing literature and modified to fit the study context to ensure an adequate level of measurement validity. The measurement items are presented in Table 6. The scales for mind perception of experience and agency were drawn from Gray et al.'s (2007) study, measuring the degree to which participants believe a design entity displays two dimensions of mind. The scale for design expertise

was drawn from Schreier et al.'s (2012) and Ratneshwar and Chaiken's (1991) studies, measuring participants' perceptions of the design expertise of those who designed the product. In addition to product attitude and purchase intention, brand attitude was also used as consumer responses toward the designed product. Five semantic differential items drawn from Chae and Hoegg's (2013) study were used to measure product attitude, each on a 7-point scale. Three items drawn from Schlosser et al.'s (2006) study were used to measure purchase intention. Four semantic differential items measuring brand attitude were drawn from Mitchell and Olson's (1981) studies, employing a 7-point scale. Next, participants' perceived threats from AI were measured using six items adopted from van Esch et al.'s (2021b) study.

As potential covariates, familiarity with AI services (Belanche et al., 2019), experience in product design (Page & Uncles, 2014), and fashion involvement (O'cass, 2004) were measured. Participants' gender and age were also considered as potential covariates. Controlling for potential confounding effects other than the hypothesized effects help achieve internal validity of the research, as it will ensure that the changes in the dependent variables result only from the hypothesized effects.

The same manipulation check items used in Pretest 2 were included: a single item from Choi et al.'s (2021) study for design entity and two scales from Baltas et al.'s (2017) and Wang and Wallendorf's (2006) studies. All multi-item scales were averaged to create a single index for each measure.

Table 6

Measurement Items

Constructs	Items	
Mind perception of Experience[b] (Gray et al., 2007)	*In your opinion, how much is AI/designer capable of the following?*	
	Mexp_1	Having experiences and being aware of things
	Mexp_2	Longing or hoping for things
	Mexp_3	Experiencing embarrassment
	Mexp_4	Feeling afraid or fearful
	Mexp_5	Feeling hungry
	Mexp_6	Experiencing joy
	Mexp_7	Experiencing physical or emotional pain
	Mexp_8	Having personality traits
	Mexp_9	Experiencing physical or emotional pleasure
	Mexp_10	Experiencing pride
	Mexp_11	Experiencing violent and uncontrolled anger
Mind perception of Agency[b] (Gray et al., 2007)	*In your opinion, how much is AI/designer capable of the following?*	
	Magen_1	Telling right from wrong
	Magen_2	Remembering things
	Magen_3	Understanding how others feel
	Magen_4	Conveying thoughts to others
	Magen_5	Making plans
	Magen_6	Exercising self-restraint over impulses
	Magen_7	Thinking
Perceived design expertise[a] (Ratneshwar & Chaiken, 1991; Schreier et al., 2012)	*Please indicate how much you agree with each statement about AI/designer*.	
	DesExp_1	In my opinion, the AI/designer have very high design expertise
	DesExp_2	In my opinion, the AI/designer have the necessary skills (know-how) to design new fashion products
	DesExp_3	In my opinion, the AI/designer have competence to design new fashion products
Product attitude[c] (Chae & Hoegg, 2013)	*How would you rate the product you just saw in the scenario, on each of the following attributes?*	
	ProAtt_1	bad–good
	ProAtt_2	dislike–like
	ProAtt_3	unfavorable–favorable
	ProAtt_4	negative–positive
	ProAtt_5	unappealing–appealing
Purchase intention[a]	*Please answer the following questions about the product you imagined seeing in the scenario.*	

(Schlosser et al., 2006)	PI_1	I have a strong possibility to purchase this product
	PI_2	I am likely to purchase this product
	PI_3	I have a high intention to purchase this product
Brand attitude[c] (Mitchell & Olson, 1981)	*How would you rate the brand you saw in the scenario, on each of the following attributes?*	
	BraAtt_1	negative–positive
	BraAtt_2	dislikable–likable
	BraAtt_3	bad–good
	BraAtt_4	unfavorable–favorable
Perceived threats from AI[b] (van Esch et al., 2021b)	*Please rate the extent to which you perceive AI as being threatening in general.*	
	threat_1	Threatened
	threat_2	Attacked
	threat_3	Challenged
	threat_4	Impugned
	threat_5	Maligned
	threat_6	Unhappy
Familiarity with AI services[a] (Belanche et al., 2019)	*Please indicate how much you agree with each statement below.*	
	FamAI_1	I have used AI-powered services or activities
	FamAI_2	Throughout my life, I have had some experience with AI-powered services
	FamAI_3	I am familiar with AI or AI content (texts, audiovisuals, etc.)
Experience in product design (Page & Uncles, 2014)	*How would you rate your experience with the fashion design and/or designing products in either a professional or unprofessional (e.g., as a hobby) capacity?*	
	ExpDes_1	very little–very much
	ExpDes_2	no experience–many experience
	ExpDes_3	below average–above average
Fashion involvement[a] (O'cass, 2004)	*Please indicate how much you agree with each statement below.*	
	FasInV_1	Fashion clothing means a lot to me
	FasInV_2	I have a very strong commitment to fashion clothing that would be difficult to break
	FasInV_3	I consider fashion clothing to be a central part of my life
	FasInV_4	I think about fashion clothing a lot
	FasInV_5	For me personally fashion clothing is an important product
	FasInV_6	I am very interested in fashion clothing
	FasInV_7	Fashion clothing is important to me
	FasInV_8	Fashion clothing is an important part of my life
	FasInV_9	I would say fashion clothing is central to my identity as a person

	FasInV_10	I would say that I am often preoccupied with fashion clothing
	FasInV_11	I can really identify with fashion clothing
	FasInV_12	I am very much involved in / with fashion clothing
	FasInV_13	I find fashion clothing a very relevant product in my life
	FasInV_14	I pay a lot of attention to fashion clothing
Design entity[c] (Choi et al., 2021)	*Please indicate the extent to which the entity who designed the product was more like a computer system or a person.*	
	very machine-like, more like a computer system–very human-like, more like a person	
Self-expressive–functional product[c] (Baltas et al., 2017)	*In your opinion, is the jacket given in the scenario focusing on a self-expressive attribute or functional attribute?*	
	highly self-expressive–highly functional	
Signaling capability[a] (Wang & Wallendorf, 2006)	*Please indicate how much you agree with each statement about the product you want in the scenario.*	
	Signal_1	The product can convey one's personality to the people around him/her
	Signal_2	The product can reflect the owner's identity
	Signal_3	The product can shape the owner's image in the eyes of others
	Signal_4	The product can tell others what kind of person the owner is

Note. [a] 7-point Likert scale (1=*Strongly disagree* – 7=*Strongly agree*); [b] 7-point Likert scale (1=*Not at all* – 7=*Very much*); [c] 7-point semantic differential scale

4.2 Results

4.2.1 Preliminary Data Analysis

Exploratory Factor Analysis. Factor analyses were conducted before hypothesis testing. Although the pre-established multi-item scales from the existing literature were used in this study, exploratory factor analysis (EFA) was first performed on the sixty-three items to understand the latent structure underlying the items (Zhang et al., 2020) better and refine the measurements. Principal component analysis (PCA) estimation and oblique factor rotation method with direct oblimin criterion were used because it is the common method suggested by the literature when some factor correlation values

exceed .32 (Tabachnick & Fidell, 2007). A scree plot was plotted to display the eigenvalue explained by each component. The scree plot's elbow where the line bends was used, resulting in eleven factors. The factors with low factor loadings (<.04) were removed (Child, 2006).

The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy (.93) confirmed the appropriateness of the data sample size. The results of Bartlett's Test of Sphericity (χ^2 (n=289) = 24725.46, p<.001) showed significant correlations among some of the components, indicating suitability for factor analysis. The eleven factors accounted for 85.56% of the total variance. Most items were loaded on the desired factor consistent with the existing scales. One item from perceived agency scale (Magen_3) was removed because it was loaded on perceived experience, not perceived agency. The items cross-loaded on two or more factors were called into question, calling for further examination. The results of EFA after removing one item are shown in Table 7.

Table 7

Results of Exploratory Factor Analysis (Study 1)

Items	Components										
	1	2	3	4	5	6	7	8	9	10	11
Mexp_7	**.97**	-.02	-.02	.02	-.01	-.01	.02	-.07	-.01	-.01	-.03
Mexp_3	**.97**	-.02	-.03	.00	-.05	-.01	.00	-.06	.01	.03	-.04
Mexp_4	**.94**	.01	.00	.00	-.04	.05	.05	-.01	.02	.00	-.02
Mexp_2	**.93**	-.02	.02	.02	.02	.03	-.01	-.02	.00	-.05	-.04
Mexp_5	**.93**	-.01	.02	-.02	-.01	.00	.01	-.05	.02	-.02	-.07
Mexp_9	**.93**	-.03	-.04	.01	.02	.01	-.02	-.03	-.01	-.06	-.04
Mexp_11	**.93**	.02	-.01	-.04	.01	.03	.03	.03	.06	.09	.06
Mexp_6	**.91**	-.02	-.03	.02	.01	.00	-.06	.00	-.01	-.05	-.05
Mexp_10	**.90**	-.01	.01	.04	.03	-.01	-.03	-.04	.03	-.09	-.04
Mexp_8	**.82**	.00	-.03	.05	.06	.04	-.04	.10	.00	-.02	-.02
Mexp_1	**.77**	.01	.03	.02	.06	.02	-.03	.19	.02	-.10	-.01
Magen_1	**.54**	.06	-.09	-.03	.02	-.07	-.02	**.47**	-.01	-.07	.05
FasInV_13	-.02	**.97**	.06	.03	.01	-.02	.03	-.03	-.01	-.06	-.01

FasInV_1	.00	**.95**	.00	.01	.02	.00	-.01	.01	-.03	-.03	-.02
FasInV_7	.00	**.95**	-.06	.02	-.01	.03	.03	.03	.00	.01	.03
FasInV_11	.05	**.94**	.05	.00	-.02	.05	.05	-.02	.05	-.03	.09
FasInV_5	-.01	**.94**	-.01	.00	.01	.01	.04	.02	.01	-.04	.05
FasInV_8	.00	**.93**	.00	-.01	.00	.01	-.03	.03	-.02	.01	.01
FasInV_9	.05	**.93**	.01	-.02	.00	.00	-.01	-.05	.00	-.02	.00
FasInV_6	-.01	**.92**	.07	.00	.05	.00	.03	-.01	-.01	-.02	-.03
FasInV_4	-.04	**.92**	-.01	.02	-.04	.01	-.01	.01	-.01	.01	-.05
FasInV_14	-.02	**.91**	.03	.00	.00	-.01	-.02	.00	.04	.01	.00
FasInV_3	.00	**.89**	-.09	-.02	-.04	-.04	-.07	-.02	-.03	.05	-.07
FasInV_12	.03	**.89**	-.03	-.05	.00	.02	-.07	.00	.03	.08	-.03
FasInV_10	-.04	**.87**	-.04	.01	.02	-.02	-.04	.02	-.04	.01	.02
FasInV_2	-.05	**.85**	-.02	.01	.04	.01	-.08	-.01	.04	.03	.00
BraAtt_4	-.01	-.01	**-.92**	-.02	.01	.01	.00	-.01	.00	-.04	-.03
BraAtt_1	-.03	.01	**-.92**	.00	-.01	.00	-.01	.03	.01	-.06	.00
BraAtt_2	.01	.01	**-.92**	.00	.00	.01	-.01	-.01	.03	-.05	.02
BraAtt_3	.03	.01	**-.90**	.02	.00	.00	.01	-.04	.05	-.05	-.02
threat_2	.02	.02	.01	**.90**	.00	.01	.07	-.04	.05	.14	-.09
threat_5	-.03	-.03	-.08	**.89**	.01	.03	.02	.01	.06	.10	.02
threat_4	.06	.01	-.09	**.87**	.01	-.06	.02	-.05	.02	.04	.04
threat_1	.04	-.03	.10	**.86**	-.03	-.02	-.01	-.04	-.05	-.06	-.06
threat_3	-.03	-.01	-.01	**.80**	.05	.04	-.08	.12	-.08	-.17	.13
threat_6	-.03	.05	.10	**.76**	-.03	-.04	-.02	-.02	-.02	-.02	-.05
signal_2	.07	.03	.05	.00	**.93**	-.03	.02	-.03	-.01	-.03	.05
signal_1	-.02	-.04	.02	.02	**.92**	.02	-.02	.05	.00	-.01	.02
signal_3	.00	.02	.04	-.06	**.89**	.01	.00	-.02	.03	-.03	-.01
signal_4	-.07	.02	-.11	.02	**.87**	.02	-.01	-.03	-.01	.09	-.09
FamAI_1	.04	.06	-.01	.03	.01	**.92**	.05	.05	.02	-.02	.09
FamAI_2	.05	-.01	.04	-.03	-.01	**.89**	.01	-.02	.04	-.01	-.02
FamAI_3	-.02	-.02	-.04	-.02	.02	**.83**	-.08	-.03	-.06	.05	-.11
ExpDes_2	-.01	.00	-.01	.00	.02	-.01	**-.97**	-.02	.02	.05	-.02
ExpDes_3	-.02	.01	.01	-.02	-.01	.02	**-.95**	.02	.02	-.05	.03
ExpDes_1	.04	.05	.00	.01	.00	.01	**-.95**	-.03	.00	.02	.00
Magen_2	-.19	-.06	.00	-.04	-.01	.05	.04	**.91**	.04	-.06	-.04
Magen_4	.26	.06	.02	.07	.01	-.02	-.02	**.58**	.15	.06	-.20
Magen_5	.26	.07	-.10	.04	.00	.00	.06	**.54**	-.04	.06	-.23
Magen_6	**.41**	.04	-.09	-.02	.06	-.08	.03	**.51**	-.01	.03	-.04
Magen_7	.38	.01	.06	.14	-.01	-.03	-.05	**.49**	-.03	-.14	-.13
PI_3	.03	.03	-.01	-.01	.01	.00	.02	-.01	**.95**	-.02	.00
PI_2	-.02	.00	-.02	.01	.01	-.03	-.05	.01	**.95**	-.03	.01
PI_1	-.02	-.02	-.01	.01	.00	.04	-.01	.02	**.93**	-.05	-.02
ProAtt_1	.03	.01	-.07	-.01	-.03	.03	.02	.01	.05	**-.86**	.01
ProAtt_4	.02	.05	-.04	.00	-.02	-.02	.01	-.02	.05	**-.85**	-.08
ProAtt_3	.03	-.02	-.10	-.02	.00	-.01	.01	-.01	.06	**-.81**	-.07
ProAtt_2	.00	-.01	-.09	-.03	.01	.01	-.03	-.02	.04	**-.78**	-.13
ProAtt_5	.04	-.02	-.10	.00	.07	-.02	.00	.02	.11	**-.76**	-.01
DesExp_3	.00	-.02	-.05	.04	.03	.05	.00	.07	.06	-.11	**-.80**
DesExp_2	.03	.01	.01	.01	.05	.07	.03	.04	.00	-.19	**-.80**
DesExp_1	.15	-.01	-.11	-.04	.04	.00	-.04	.04	.07	-.01	**-.74**

Eigenvalue	17.70	12.82	6.59	3.84	3.14	2.23	1.94	1.54	1.37	1.06	0.82
% of Variance Extracted	28.55	20.68	10.63	6.20	5.06	3.60	3.13	2.49	2.21	1.70	1.32

Note. Bold numbers are the factor loadings higher than .40.

Cronbach's Alpha. The Cronbach's alpha for each construct with the final measurement items (see also Confirmatory Factor Analysis below) was calculated to test the construct validity and internal consistency of the measurements. All alpha values were larger than the generally accepted value of .70, indicating good construct validity and reliability (Cortina, 1993). Table 8 shows the results of EFA with the final measurements and the Cronbach's alpha values.

Table 8

Results of Exploratory Factor Analysis with Final Items (Study 1)

Items	Components										
	1	2	3	4	5	6	7	8	9	10	11
Mexp_7	**.99**	-.01	-.02	.02	-.01	-.02	.02	-.02	.05	.00	-.03
Mexp_3	**.99**	-.01	-.03	.00	-.04	-.02	.00	.00	.04	.04	-.03
Mexp_5	**.95**	.01	.02	-.02	-.01	-.01	.01	.01	.03	-.02	-.06
Mexp_4	**.95**	.02	.00	.01	-.04	.04	.04	.01	.00	.01	-.01
Mexp_9	**.92**	-.03	-.03	.01	.02	.01	-.02	-.02	-.01	-.05	-.03
Mexp_2	**.91**	-.01	.02	.02	.02	.02	-.01	.00	-.03	-.05	-.02
Mexp_11	**.90**	.02	-.01	-.04	.01	.02	.02	.05	-.06	.10	.06
Mexp_10	**.88**	.00	.01	.05	.03	-.01	-.03	.02	-.02	-.08	-.03
Mexp_6	**.88**	-.02	-.03	.02	.01	.00	-.06	-.02	-.06	-.05	-.03
Mexp_8	**.76**	.00	-.03	.04	.06	.04	-.04	.00	-.17	-.01	.00
Mexp_1	**.65**	.01	.04	.01	.06	.02	-.03	.02	-.29	-.10	.02
FasInV_13	.01	**.97**	.06	.03	.01	-.03	.03	-.02	.05	-.06	-.01
FasInV_7	.01	**.95**	-.06	.02	-.01	.02	.03	.00	-.01	.01	.03
FasInV_1	.00	**.95**	.00	.01	.02	.00	-.01	-.03	-.03	-.03	-.01
FasInV_11	.05	**.94**	.05	.00	-.02	.05	.05	.05	.02	-.03	.08
FasInV_5	-.02	**.94**	-.01	.00	.01	.01	.04	.01	-.04	-.04	.05
FasInV_9	.07	**.93**	.01	-.02	.00	.00	-.01	.00	.06	-.02	.00
FasInV_6	.00	**.92**	.07	.00	.05	-.01	.03	-.01	.01	-.02	-.03
FasInV_8	-.02	**.92**	.00	-.02	.00	.01	-.03	-.02	-.06	.00	.02
FasInV_4	-.03	**.92**	-.01	.03	-.04	.00	-.01	-.01	.01	.01	-.05
FasInV_14	-.01	**.91**	.02	.00	.00	-.01	-.02	.04	.00	.02	-.01
FasInV_3	.02	**.89**	-.09	-.02	-.04	-.04	-.08	-.03	.01	.05	-.07

FasInV_12	.04	**.89**	-.04	-.05	.00	.02	-.07	.03	.00	.08	-.03
FasInV_10	-.07	**.86**	-.03	.00	.02	-.02	-.04	-.03	-.05	.01	.03
FasInV_2	-.05	**.85**	-.02	.01	.04	.01	-.08	.04	.00	.03	.00
BraAtt_4	.01	.00	**-.92**	-.01	.02	.00	.00	.01	.01	-.04	-.03
BraAtt_2	.02	.02	**-.91**	.00	.00	.01	-.01	.03	.02	-.05	.01
BraAtt_1	-.05	.00	**-.91**	.00	-.01	.00	-.01	.02	-.07	-.06	.01
BraAtt_3	.05	.02	**-.89**	.02	.00	.00	.01	.05	.03	-.05	-.02
threat_2	.05	.02	.01	**.90**	.01	.00	.07	.05	.04	.14	-.09
threat_5	-.02	-.02	-.08	**.88**	.01	.03	.02	.06	-.01	.11	.01
threat_4	.08	.02	-.09	**.87**	.01	-.07	.02	.02	.04	.04	.04
threat_1	.08	-.02	.09	**.86**	-.03	-.02	-.01	-.05	.06	-.06	-.06
threat_3	-.09	-.02	-.01	**.79**	.04	.05	-.08	-.08	-.15	-.17	.12
threat_6	-.02	.04	.10	**.76**	-.03	-.04	-.03	-.02	-.02	-.03	-.03
signal_2	.06	.02	.05	.01	**.93**	-.03	.02	-.01	.00	-.03	.05
signal_1	-.04	-.04	.02	.02	**.91**	.02	-.02	.00	-.05	-.01	.02
signal_3	.03	.02	.04	-.05	**.89**	.00	.00	.03	.05	-.03	-.02
signal_4	-.04	.02	-.11	.03	**.87**	.02	-.01	-.01	.03	.08	-.08
FamAI_1	.01	.06	-.01	.03	.01	**.92**	.05	.02	-.02	-.02	.08
FamAI_2	.05	-.01	.04	-.03	-.01	**.89**	.01	.04	.05	-.01	-.02
FamAI_3	-.04	-.03	-.03	-.02	.02	**.84**	-.09	-.06	.00	.04	-.08
ExpDes_2	.01	.01	-.01	.00	.02	-.01	**-.97**	.02	.03	.05	-.02
ExpDes_3	-.02	.01	.01	-.02	-.01	.02	**-.95**	.02	-.02	-.05	.02
ExpDes_1	.05	.05	.00	.01	.00	.01	**-.95**	.00	.03	.02	.00
PI_3	.02	.03	-.01	-.01	.01	.00	.01	**.95**	-.01	-.02	.01
PI_2	-.02	.00	-.02	.01	.01	-.03	-.05	**.95**	-.01	-.03	.01
PI_1	-.01	-.02	-.01	.01	.00	.04	-.01	**.93**	.00	-.05	-.02
Magen_4	-.03	.02	.04	.04	-.01	.02	-.01	.16	**-.83**	.04	-.12
Magen_6	.13	.00	-.07	-.05	.05	-.05	.04	-.01	**-.76**	.01	.03
Magen_5	.02	.04	-.08	.01	-.01	.02	.06	-.03	**-.74**	.05	-.17
Magen_7	.12	-.02	.07	.11	-.02	.01	-.04	-.02	**-.73**	-.15	-.06
Magen_1	.29	.03	-.07	-.05	.01	-.04	-.01	-.01	**-.66**	-.07	.10
ProAtt_1	.00	.00	-.07	-.01	-.03	.04	.02	.05	-.03	**-.87**	.02
ProAtt_4	.03	.05	-.04	.00	-.02	-.02	.02	.05	.03	**-.86**	-.07
ProAtt_3	.04	-.02	-.10	-.02	.00	-.01	.01	.06	.01	**-.82**	-.06
ProAtt_2	.01	-.01	-.09	-.03	.01	.01	-.03	.04	.01	**-.79**	-.12
ProAtt_5	.02	-.02	-.10	-.01	.07	-.02	.00	.11	-.02	**-.77**	-.01
DesExp_3	.05	-.02	-.05	.04	.03	.05	.00	.06	-.13	-.13	**-.73**
DesExp_2	.06	.01	.00	.01	.05	.08	.03	.00	-.11	-.21	**-.72**
DesExp_1	.19	-.01	-.11	-.04	.05	.00	-.04	.07	-.12	-.03	**-.67**
Eigenvalue	17.58	12.78	6.59	3.84	3.14	2.21	1.88	1.40	1.25	1.00	0.80
% of Variance Extracted	28.82	20.95	10.80	6.29	5.14	3.62	3.08	2.30	2.04	1.63	1.30
Cronbach's α	.98	.98	.97	.92	.92	.87	.97	.97	.92	.97	.94

Note. Bold numbers are the factor loadings higher than .40.

Confirmatory Factor Analysis. Confirmatory factor analysis (CFA) with maximum-likelihood estimation method was performed to confirm the a priori relationship between the observed variables and the latent factors (Chen et al., 2020) using AMOS 29. The measurement model showed an adequate fit, but one item from perceived agency (Magen_2) was removed because of a low standardized loading (.49) to its latent variable. The final model fit indices showed a good fit (χ^2=2345.52, *df*=1680; χ^2/df=1.40; CFI=.97; NNFI=.97; RMSEA=.04; SRMR=.03). The widely accepted index thresholds were applied (e.g., Bentler, 1990; Gerbing & Anderson, 1992; Thompson, 2004). First, χ^2 significant test evaluated the fit of a single model, providing χ^2 and χ^2/df (<2-3). The *non-normed fit index* (NNFI; Tucker & Lewis, 1973; general threshold: >.95), and *comparative fit index* (CFI; Bentler, 1990; >.90) compared the model fit for the tested model against the one for the baseline model. *Root-mean-square error of approximation* (RMSEA; Steiger & Lind, 1980; <.08) was used to estimate the fit of model parameters for reproducing the population covariances. *Standardized root-mean-square residual* (SRMR; Hu & Bentler, 1998; <.08) showed the model fit, indicating the square-root of the difference between the residuals of the sample covariance matrix and the hypothesized model. *Average variance extracted* (AVE; Fornell & Larcker, 1981; >.50) was provided to examine the amount of variance captured by a construct.

The convergent validity of the constructs was supported. First, the composite reliabilities for all constructs were larger than .70. Second, the items of each scale were loaded on its construct with significant loadings (p<.001; see Table 9). Lastly, the average variance extracted (AVE) for each construct exceeded the benchmark of .50 (Hair et al., 2019). The discriminant validity of the constructs was supported as the

variance extracted was larger than the squared correlation of latent variables for all constructs (Fornell & Larcker, 1981). Table 10 shows the descriptive statistics, AVE, correlations, squared correlations, and composite reliabilities of the latent factors.

Although the correlation between perceived experience and agency was high (.82), the author considered the two constructs separately for two reasons. First, mind perception theory literature has shown that some items have relatively high EFA factor loadings on both perceived experience and agency (e.g., the item 'Consciousness' loaded .71 on experience and .69 on agency; see Supporting Online Material by Gray et al., 2007). Second, as described above, the discriminant validity test indicates the appropriate degree to which measures of experience and agency are distinct (see Table 10). Instead, given that perceived experience and perceived agency are the sub-dimensions of mind perception, the index of mind perception (α=.98) was additionally computed by averaging the indices of perceived experience and agency and used in the additional analyses.

Table 9

Confirmatory Factor Analysis: Standardized Factor Loadings (Study 1)

Construct	Item	Loading	Construct	Item	Loading
Signaling capability	signal_1	.88	Brand attitude	BraAtt_1	.95
	signal_2	.89		BraAtt_2	.95
	signal_3	.86		BraAtt_3	.95
	signal_4	.84		BraAtt_4	.95
Mind perception of Experience	Mexp_1	.90	Perceived threats from AI	threat_1	.85
	Mexp_2	.97		threat_2	.86
	Mexp_3	.94		threat_3	.74
	Mexp_4	.92		threat_4	.83
	Mexp_5	.93		threat_5	.89
	Mexp_6	.98		threat_6	.77

	Mexp_7	.95	Familiarity with AI services	FamAI_1	.87
	Mexp_8	.91		FamAI_2	.85
	Mexp_9	.97		FamAI_3	.78
	Mexp_10	.96	Experience in product design	ExpDes_1	.97
	Mexp_11	.85		ExpDes_2	.97
Mind perception of Agency	Magen_1	.83		ExpDes_3	.93
	Magen_4	.84	Fashion involvement	FasInV_1	.95
	Magen_5	.79		FasInV_2	.89
	Magen_6	.78		FasInV_3	.91
	Magen_7	.87		FasInV_4	.91
Perceived design expertise	DesExp_1	.88		FasInV_5	.92
	DesExp_2	.94		FasInV_6	.90
	DesExp_3	.94		FasInV_7	.95
Product attitude	ProAtt_1	.92		FasInV_8	.93
	ProAtt_2	.92		FasInV_9	.92
	ProAtt_3	.95		FasInV_10	.88
	ProAtt_4	.94		FasInV_11	.91
	ProAtt_5	.91		FasInV_12	.92
Purchase intention	PI_1	.96		FasInV_13	.93
	PI_2	.96		FasInV_14	.92
	PI_3	.97		Total: 61 items	

Common Method Bias. Common method bias could be a concern when both independent and dependent variables were measured in a single questionnaire (Podsakoff et al., 2003). The presence of common method bias was tested using Harman's one-factor test. The total variance extracted by one factor using the final 61 items was 28.82%, which is less than the recommended threshold of 50% (Podsakoff & Organ, 1986). Thus, common method bias was not a major concern in this study.

Table 10

AVE, Factor Correlations, and Composite Reliabilities (Study 1)

Construct	1	2	3	4	5	6	7	8	9	10	11
1. Signaling capability	**.76**	.02	.03	.06	.02	.03	.02	.00	.05	.03	.06
2. Mind perception of Experience	.14	**.87**	.67	.42	.19	.07	.10	.03	.01	.00	.00
3. Mind perception of Agency	.16	.82	**.68**	.48	.20	.08	.11	.04	.00	.00	.01
4. Perceived design expertise	.25	.65	.69	**.84**	.43	.18	.24	.00	.07	.00	.00
5. Product attitude	.14	.43	.45	.66	**.86**	.41	.58	.00	.01	.00	.00
6. Purchase intention	.16	.26	.28	.43	.64	**.93**	.36	.01	.01	.02	.03
7. Brand attitude	.16	.31	.33	.49	.76	.60	**.90**	.01	.01	.02	.03
8. Perceived threats from AI	.01	.18	.20	.06	-.04	-.07	-.10	**.68**	.02	.00	.00
9. Familiarity with AI services	.22	.11	.07	.26	.09	.11	.09	-.13	**.70**	.03	.02
10. Experience in product design	.18	.06	.02	.05	.06	.15	.13	.03	.18	**.92**	.27
11. Fashion involvement	.25	.04	.11	.02	.04	.18	.16	.06	.16	.52	**.84**
Mean	4.79	3.85	4.77	5.50	5.29	4.08	4.92	2.55	5.00	2.82	2.90
SD	1.25	2.41	1.87	1.37	1.24	1.75	1.31	1.26	1.30	1.72	1.61
Composite Reliability[a]	.92	.98	.91	.94	.97	.97	.97	.93	.87	.97	.98

Note. Average variance extracted[b] (AVE) values are bold numbers on the diagonal axis. Values below the diagonal are correlations. Values above the diagonal are squared correlations.

[a] Composite Reliability = $(\sum \text{standardized loading})^2 / (\sum \text{standardized loading})^2 + \sum \text{measurement error}$

[b] Variance Extracted = $\sum (\text{standardized loading})^2 / \sum (\text{standardized loading})^2 + \sum \text{measurement error}$

4.2.2 Hypothesis Testing

Manipulation Check. The manipulation of design entity and product type was successful. Design entity in the AI condition was perceived as less human-like (i.e., more machine-like) than the human condition (M_{AI}=1.92 vs. M_{human}=5.70; $t(287)$=-21.41, p<.001). A fashionable jacket was perceived to have more self-expressive (i.e., less functional) attributes ($M_{fashionable}$=3.28 vs. $M_{insulated}$=5.66; $F(1, 287)$=153.54, p<.001) and to be capable of signaling one's identity ($M_{fashionable}$=5.23 vs. $M_{insulated}$=4.38; $F(1, 287)$=38.42, p<.001) than an insulated jacket.

Covariates and Assumption Check. MANCOVA was performed to test the effect of design entity on consumer responses (H1) and mind perception (H2a) and the moderating effect of product type (H4a). The two categorical variables, design entity (AI vs. human) and product type (self-expressive vs. functional), were entered as independent variables. Perceived experience, perceived agency, perceived design expertise, product attitude, purchase intention, and brand attitude were entered as dependent variables.

The potential covariates were age, gender, familiarity with AI, experience in design, and fashion involvement. All potential covariates showed a significant correlation with at least one dependent variable at a significance level of .05. Experience in product design (p=.620) and gender (p=.899) did not significantly affect the dependent variables, and thus they were excluded from the analysis. Familiarity with AI services (p<.001), fashion involvement (p<.001), and age (p<.001) showed significant effects on the dependent variables and thus were entered as covariates.

The assumptions of MANOVA and ANOVA were checked before the hypothesis testing. First, the correlations between the dependent variables were moderately high and

did not exceed .90 (see Table 10), indicating that performing MANOVA is appropriate compared to separate ANOVAs. Second, the Box's M test was used to test the MANOVA assumption of homogeneity of variance-covariance matrices. The significance level was less than the threshold of .001 ($p<.001$), indicating differences in covariances. Because MANOVA and Pillai's trace tend to be robust against heterogeneity of covariances in large balanced sample sizes (Bray & Maxwell, 1985; Tabachnick & Fidell, 2007), Pillai's trace criterion was used instead of Wilk's lambda criterion. Next, the assumption of ANOVA was checked because the results of the subsequent univariate analyses are used in case the multivariate analysis shows significant results. The homogeneity of variance assumption of ANOVA was checked by looking at Levene's test of equality of error variances. While the variances were equal across groups for product attitude ($p=.586$), purchase intention ($p=.265$), and brand attitude ($p=.646$), the test showed significant statistics for perceived experience ($p=.019$), agency ($p<.001$), and design expertise ($p<.001$). However, it is known that ANOVA on balanced data is generally robust despite the violation of the homogeneity of variance assumption if the ratio of the largest to smallest group variances is not larger than 4 (Dean & Voss, 1999; Kurilla, 2015). The ratios of the largest to smallest variances of the study conditions showed the appropriateness of interpreting the results of ANOVA (see Table 11).

Table 11

Ratio of the Largest to Smallest Group Variances (Study 1)

	Perceived experience	Perceived agency	Perceived design expertise	Product attitude	Purchase intention	Brand attitude
s^2_{max}/s^2_{min}	1.83	2.03	3.08	1.37	1.27	1.14

Effect of Design Entity and Product Type. The results of multivariate tests showed a significant main effect of design entity (Pillai's V=.82, p<.001, partial η^2=.82). The effect of product type (p=.630) nor the design entity × product type interaction effect (p=.794) was not significant. The following ANCOVA showed that participants formed more favorable product attitudes (M_{AI}=4.82 vs. M_{human}=5.74; F(1, 282)=47.22, p<.001, partial η^2=.14) and brand attitudes (M_{AI}=4.58 vs. M_{human}=5.25; F(1, 282)=20.99, p<.001, partial η^2=.07) and higher purchase intentions (M_{AI}=3.74 vs. M_{human}=4.41; F(1, 282)=11.22, p<.001, partial η^2=.04) toward human-designed (vs. AI-designed) jacket, supporting H1. Human designer was perceived to have higher experience (M_{AI}=1.65 vs. M_{human}=5.97; F(1, 282)=1249.72, p<.001, partial η^2=.82), agency (M_{AI}=3.45 vs. M_{human}=6.03; F(1, 282)=263.58, p<.001, partial η^2=.48), and design expertise (M_{AI}=4.67 vs. M_{human}=6.31; F(1, 282)=168.80, p<.001, partial η^2=.37). Thus, H2a was supported. H4a was rejected because the design entity × product type interaction was not significant.

Mediation of Mind Perception and Perceived Design Expertise. PROCESS macro (Hayes, 2017) was used to test the mediation of mind perception (H2b) and the serial mediation of mind perception and perceived design expertise (H3) on the relationship between design entity and consumer responses. Familiarity with AI services, fashion involvement, and age were entered as covariates across the models.

Considering perceived experience and agency are the sub-dimensions of mind perception (see 2.2 and 4.2.1), the indices of mind perception were first used before separating perceived experience and agency. Simple mediation analyses (Model 4) with 5,000 bootstrap samples were performed to test the mediation of mind perception. The indirect effects of design entity through mind perception were significant on product

attitude (indirect effect: 1.11, 95% CI = [0.5987, 1.5887]), purchase intention (indirect effect: 1.27, 95% CI = [0.5674, 1.9740]), and brand attitude (indirect effect: 0.91, 95% CI = [0.3120, 1.4565]). Next, serial mediation analyses (Model 6) with 5,000 bootstrap samples were performed. The indirect effects of design entity through mind perception and perceived design expertise were significant on product attitude (indirect effect: 0.80, 95% CI = [0.5081, 1.1077]), purchase intention (indirect effect: 0.81, 95% CI = [0.4835, 1.2041]), and brand attitude (indirect effect: 0.68, 95% CI = [0.4147, 0.9663]). The mediations were significant when perceived experience and agency were separately entered as the mediators, as shown in Table 12. Thus, the results supported H2b and H3.

Table 12

Separate Mediation Analyses (Study 1)

Mediation	Indirect effect	BootLLCI	BootULCI
design entity → experience → product attitude	1.02*	0.4812	1.5523
design entity → experience → purchase intention	1.31*	0.5219	2.1368
design entity → experience → brand attitude	0.85*	0.2249	1.4930
design entity → agency → product attitude	0.55*	0.2771	0.8176
design entity → agency → purchase intention	0.52*	0.1348	0.9151
design entity → agency → brand attitude	0.44*	0.1276	0.7400
design entity → experience → design expertise → product attitude	0.65*	0.3407	0.9844
design entity → experience → design expertise → purchase intention	0.65*	0.3260	1.0267
design entity → experience → design expertise → brand attitude	0.54*	0.2857	0.8295
design entity → agency → design expertise → product attitude	0.48*	0.3154	0.6722
design entity → agency → design expertise → purchase intention	0.51*	0.3037	0.7500
design entity → agency → design expertise → brand attitude	0.41*	0.2571	0.5990

Note. Asterisk (*) indicates significant indirect effects.

Model 80 with 5,000 bootstrap samples was performed to test separate parallel mediations of perceived experience and perceived agency and serial mediation simultaneously. Design entity as an independent variable, perceived experience and perceived agency as the first two parallel mediators, and perceived design expertise as the second serial mediator were entered (see Figure 6). The results for all three dependent variables (DVs) showed significant mediation of design expertise (design entity → perceived design expertise → DVs) and significant serial mediation of perceived agency and design expertise (design entity → perceived agency → perceived design expertise → DVs). However, the serial mediation of perceived experience and design expertise (design entity → perceived experience → perceived design expertise → DVs) became non-significant. The results mean that when simultaneously analyzing all parallel and serial mediators in one model, the mediating effect of perceived design expertise and the serial mediating effect of perceived agency and design expertise overrides other mediation effects. The results of the Model 80 analyses are presented in Table 13.

Figure 6

Parallel and Serial Mediation Analysis Model (Study 1)

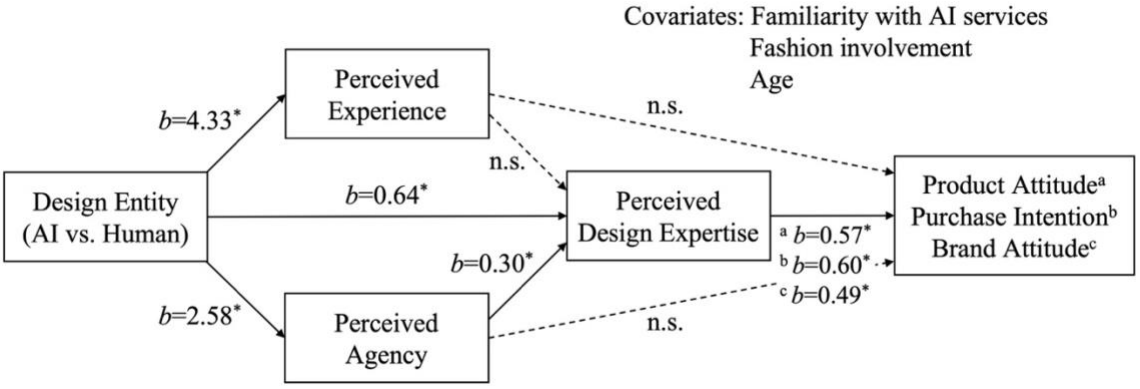


Table 13

Parallel and Serial Mediation Analysis Results (Study 1)

	Indirect effect	BootSE	BootLLCI	BootULCI
DV: Product attitude				
Total effect of design entity on DV: .9268, t=6.87, p<.001; direct effect: p=.148				
Total indirect effect	1.31*	0.2373	0.8504	1.7841
design entity → experience → product attitude	0.40	0.2603	-0.0923	0.9214
design entity → agency → product attitude	-0.03	0.1483	-0.3108	0.2665
design entity → design expertise → product attitude	0.37*	0.1483	0.0974	0.6879
design entity → experience → design expertise → product attitude	0.12	0.1543	-0.1774	0.4345
design entity → agency → design expertise → product attitude	0.45*	0.0976	0.2680	0.6509
DV: Purchase intention				
Total effect of design entity on DV: .6650, t=3.34, p=.01; direct effect: -.9774, t=-2.25, p=.025				
Total indirect effect	1.64*	0.3842	0.9145	2.4311
design entity → experience → purchase intention	0.85	0.4603	-0.0039	1.7957
design entity → agency → purchase intention	-0.19	0.2253	-0.6303	0.2575
design entity → design expertise → purchase intention	0.38*	0.1558	0.1178	0.7188
design entity → experience → design expertise → purchase intention	0.13	0.1569	-0.1772	0.4431
design entity → agency → design expertise → purchase intention	0.47*	0.1216	0.2558	0.7311
DV: Brand attitude				
Total effect of design entity on DV: .6689, t=4.58, p<.001; direct effect: p=.167				
Total indirect effect	1.10*	0.2943	0.5076	1.6688
design entity → experience → brand attitude	0.36	0.3264	-0.2771	1.0025
design entity → agency → brand attitude	-0.06	0.1692	-0.3843	0.2848
design entity → design expertise → brand attitude	0.31*	0.1225	0.0909	0.5722
design entity → experience → design expertise → brand attitude	0.10	0.1273	-0.1454	0.3538
design entity → agency → design expertise → brand attitude	0.38*	0.0941	0.2149	0.5811

Note. Asterisk (*) indicates significant indirect effects.

Moderation of Product Type and Perceived Threats from AI. PROCESS macro (Hayes, 2017) was used to test the moderation of perceived threats from AI (H5a) and the moderated serial mediation by product type (H4b) and perceived threats from AI (H5b). Familiarity with AI services, fashion involvement, and age were entered as covariates across the models.

Model 1 with 5,000 bootstrap samples was performed with design entity as independent variable, perceived threats from AI as a moderator, and the three dependent variables. The design entity × perceived threats interaction was not significant on product attitude, purchase intention, and brand attitude (p>.05). The human-designed jacket was more positively evaluated than the AI-designed one for all participants with low (-1SD), moderate (mean), and high (+1SD) levels of perceived threats from AI. Participants formed more favorable product attitudes (b=1.02, t=3.31, p=.001) and brand attitude (b=0.76, t=2.31, p=.022), purchase intention (b=0.97, t=2.14, p=.033) toward the human-designed jacket than AI-designed jacket, regardless of perceived threats from AI. Thus, H1 was again supported but H5a was not supported.

Model 87 with 5,000 bootstrap samples was performed to test the moderated serial mediation. Design entity as an independent variable, perceived experience or perceived agency as the first serial mediator, perceived design expertise as the second serial mediator, and product type or perceived threats from AI as a moderator were entered (see Figure 7). The results of moderated serial mediation by product type are presented in Table 14. Self-expressive product was coded as 1 and functional product was coded as 2. The indices of moderated serial mediation by product type were not significant for all three dependent variables. The serial mediation of experience or agency

and design expertise (design entity → experience / agency → design expertise → product attitude) was significant across product attitude, purchase intention, and brand attitude, regardless of the product type (see Table 14). Thus, H4b was not supported.

Figure 7

Moderated Serial Mediation Analysis Model

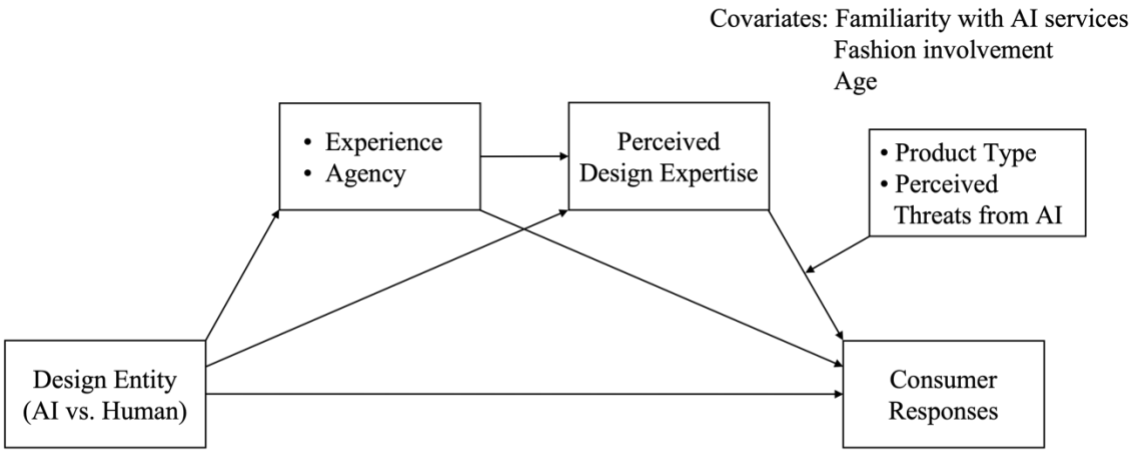


Table 14

Serial Mediation Moderated by Product Type

Mediation Paths	Moderated mediation index			Conditional serial mediation (Model 87)					
				Self-expressive product			Functional product		
	IE	LLCI	ULCI	IE	LLCI	ULCI	IE	LLCI	ULCI
design entity → experience → design expertise → product attitude	-0.12	-0.3543	0.0809	0.71*	0.3800	1.0872	0.59*	0.2997	0.9253
design entity → experience → design expertise → purchase intention	-0.21	-0.5424	0.0633	0.76*	0.3850	1.2248	0.55*	0.2488	0.9413
design entity → experience → design expertise → brand attitude	-0.00	-0.2197	0.2165	0.54*	0.2824	0.8553	0.54*	0.2716	0.8623
design entity → agency → design expertise → product attitude	-0.09	-0.2324	0.0733	0.53*	0.3544	0.7238	0.44*	0.2730	0.6519
design entity → agency → design expertise → purchase intention	-0.15	-0.3737	0.0538	0.60*	0.3690	0.8676	0.44*	0.2226	0.7019
design entity → agency → design expertise → brand attitude	-0.00	-0.1625	0.1594	0.41*	0.2423	0.6133	0.41*	0.2359	0.6164

Note. Asterisk (*) indicates significant indirect effects. IE: indirect effect

The results of moderated serial mediation by perceived threats from AI are presented in Table 15. The analyses revealed different results between the dependent variables as well as perceived experience and agency. When product attitude was entered as the dependent variable, moderation of AI threat was significant in the serial mediation of experience and design expertise (design entity → experience → design expertise → product attitude; index: 0.12, 95% CI = [0.0199, 0.2475]) and agency and design expertise (design entity → agency → design expertise → product attitude; index: 0.09, 95% CI = [0.0165, 0.1804]). As expected, serial mediation effect was stronger for participants with high (+1SD) perceived threats from AI, followed by moderate (mean) and low (-1SD) perceived threats from AI (see Table 15). However, moderated mediation was not significant for purchase intention and brand attitude. The simple mediation of perceived experience or agency and direct effect of design entity became non-significant on product attitudes across the models. Unexpectedly, one exception was when agency was entered as the first mediator; the mediation of perceived design expertise remained significant and was moderated by perceived threats from AI (design entity → design expertise → product attitude; index: 0.09, 95% CI = [0.0182, 0.1681]). Consistent with the hypothesis, the mediation was stronger for those with higher perceived threats from AI. Thus, H5b was supported for product attitude, but not for purchase intention and brand attitude.

Table 15

Serial Mediation Moderated by Perceived Threats from AI

Mediation Paths	Moderated mediation index			Conditional serial mediation (Model 87)								
				Low (-1SD) perceived AI threats			Moderate (mean) perceived AI threats			High (+1SD) perceived AI threats		
	IE	LLCI	ULCI	IE	LLCI	ULCI	IE	LLCI	ULCI	IE	LLCI	ULCI
design entity → experience → design expertise → product attitude	0.12*	0.0199	0.2475	0.54*	0.2744	0.8598	0.70*	0.3652	1.0569	0.85*	0.4286	1.3231
design entity → experience → design expertise → purchase intention	-0.01	-0.1341	0.1163	0.65*	0.3127	1.0385	0.63*	0.3199	1.0343	0.62*	0.2616	1.0949
design entity → experience → design expertise → brand attitude	0.07	-0.0174	0.1858	0.47*	0.2279	0.7577	0.57*	0.2827	0.8812	0.66*	0.3135	1.0598
design entity → agency → design expertise → product attitude	0.09*	0.0165	0.1804	0.40*	0.2392	0.5801	0.52*	0.3425	0.7184	0.63*	0.4003	0.9014
design entity → agency → design expertise → purchase intention	-0.01	-0.1035	0.0857	0.51*	0.2817	0.7664	0.50*	0.2920	0.7348	0.49*	0.2444	0.7660
design entity → agency → design expertise → brand attitude	0.05	-0.0165	0.1298	0.36*	0.1954	0.5411	0.42*	0.2578	0.6084	0.49*	0.2875	0.7195

Note. Asterisk (*) indicates significant moderated mediation or indirect effects. IE: indirect effect

4.3 Discussion

The hypothesis testing results of Study 1 are provided in Table 16. Study 1 tested whether consumer responses toward fashion products differ depending on design entity (AI versus humans; H1) using hypothetical shopping scenarios and fictitious brand names. As hypothesized, participants in the human condition formed more favorable product and brand attitudes and higher purchase intentions. These results are consistent with the results of the pilot study. The Study 1 results confirmed consumers infer higher levels of mind capacity to feel and sense emotions and intentional ability to act, plan, and think to humans than AI (H2a). Furthermore, the results showed that mind perception explains the effect of design entity (H2b). Consumers prefer human-designed fashion products to AI-designed ones because they perceive higher experience and agency from humans than AI. The findings contribute to mind perception theory by validating the premise of mind perception theory in the context of generative AI in the fashion design process.

Table 16

Study 1 Hypothesis Testing Results

Hypotheses		Results	
H1	design entity (AI vs. Human) → consumer responses	supported	· Participants preferred human-designed products to AI-designed products, confirmed through product attitude, purchase intention, and brand attitude.
H2a	design entity (AI vs. Human) → mind perception (experience, agency)	supported	· Participants ascribed lower experience and lower agency from AI than humans.
H2b	design entity (AI vs. Human) → mind perception → consumer responses	supported	· The superior effect of human (vs. AI) design entity was explained by mind perception.
H3	design entity (AI vs. Human) → mind perception → perceived design expertise → consumer responses	supported	· The superior effect of human (vs. AI) design entity was serially explained by mind perception and perceived design expertise. · When all parallel and serial mediations were entered, the mediation of perceived design expertise and the serial mediation of perceived agency and perceived design expertise overrode other mediations.
H4a	Moderation of product type (self-expressive vs. functional) on the effect of design entity	not supported	· The superior effect of human (vs. AI) design entity was confirmed across self-expressive and functional products.
H4b	Moderation of product type (self-expressive vs. functional) on mediation	not supported	· Mind perception and perceived design expertise explained the superior effect of human (vs. AI) design entity across self-expressive and functional products.
H5a	Moderation of perceived threats from AI on the effect of design entity	not supported	· The superior effect of human (vs. AI) design entity was confirmed across participants' low, moderate, and high levels of perceived threats from AI.
H5b	Moderation of perceived threats from AI on mediation	partially supported	· Mind perception and perceived design expertise more strongly explained the superior effect of human (vs. AI) design entity for participants with higher perceived threats from AI, which was confirmed for product attitude but not for purchase intention and brand attitude.

In addition to mind perception, perceived design expertise also explains the path from design entity to consumer responses (H3). These findings are consistent with the mind perception theory literature and extend the findings by introducing perceived design expertise. The literature suggested that ascribing the mind to other entities is a pre-attributional process that identifies another characteristic that might explain or predict the entity's behavior (Epley & Waytz, 2010; Premack & Woodruff, 1978). According to Study 1 findings, ascribing the mind to AI versus humans served as a pre-attributional process that identified the extent to which the design entity was believed to have required skills and knowledge in design. Consequently, consumers perceive high experience and agency from humans than AI, which leads to higher perceived design expertise from humans, and thus evaluated human-designed products more favorably.

Interestingly, when perceived experience and agency were separately entered as parallel mediators and perceived design expertise was entered as the second serial mediator in the model, only the mediation of design expertise (design entity → design expertise → product attitude) and the serial mediation of agency and design expertise (design entity → agency → design expertise → product attitude) remained significant (see Table 13). In contrast, the sole mediation of experience or agency and the serial mediation of experience and design expertise (design entity → experience → design expertise → product attitude) became non-significant. These findings can be interpreted as that when all three mediators are examined at the same time, design expertise and agency–design expertise chain better explain the effect more than the other three. This means that, Study 1 participants' preferences for human-designed (vs. AI-designed) jackets were mainly because of the sole higher perceived design expertise or agency–

design expertise association, not mainly because of higher experience, higher agency, or higher perceived experience–design expertise association. The significant serial mediation (design entity → agency → design expertise → product attitude) was stronger than the significant sole mediation of design expertise. This finding solidifies the mind perception theory literature in that perceived agency affecting perceived design expertise is a crucial factor that explains the effect of design entity. In sum, consumers prefer human-designed (vs. AI-designed) fashion products mostly because of the higher perceived design expertise of human designers. The perceived design expertise works as a sole factor or is affected by perceived agency. These findings are meaningful in that fashion product design is seen differently from pure art in which artists' experiential ability is highly appreciated compared to perceived agency; consumers take the intentional and cognitive ability of a design entity into account more than experience when forming responses to fashion products.

The moderating effects of product type (self-expressive vs. functional) were tested in Study 1. It was hypothesized that consumers would react less negatively against AI-designed functional products than self-expressive products (H4a). Also, the mediation effect of perceived experience (vs. agency) was hypothesized to be strengthened for self-expressive (vs. functional) products (H4b). Contrary to the predictions, the results of Study 1 showed non-significant differences between the product type in consumer responses and mediation. Study 1 participants liked the product and the brand and were more willing to purchase the human-designed jacket than the AI-designed one, and this pattern was found regardless of whether it was a fashionable jacket or an insulated jacket. Perceived experience and agency and perceived design expertise mediated the effect of

design entity at a similar level regardless of the product type (see Table 14). While the different responses were hypothesized between self-expressive and functional products, consumer preference for human-designed to AI-designed products holds across the two product types in the same product category (i.e., jackets in Study 1). Some fashion products, especially apparel, are considered to have an inherently high ability to express the wearer's status, identity, or styles (Johnson et al., 2014; Lennon et al., 2017; Park et al., 2020). Thus, it is possible that algorithm aversion or appreciation in design does not occur differently in the same apparel category, although Study 1 participants perceived different levels of self-expressive versus functional attributes between the two jackets. Indeed, other studies on AI that found significant differences between product types were mainly conducted in the context of different product categories. For example, Zhang et al. (2022) compared AI-designed art paintings with clothing, and Xu and Mehta (2022) compared AI-designed clothing with automobiles. In the context of AI-enabled services, Ruan and Mezei (2022) found the differential effects of product type by comparing perfume, coat, and air fryers.

Alternatively, another possible explanation of the non-significant differences between self-expressive and functional products comes from possible resistance to some types of functional AI-led decisions. It has been consistently found that people are resistant to AI's automatically made medical decisions (Christensen, 2023; Gaube et al., 2021; Longoni et al., 2019). People are more opposed to AI-made decisions and show an illusory understanding of human decision-making when the decisions are more personal or related to health, because AI is deemed not responsible for feeling activities (Cadario et al., 2021; Christensen, 2023; Rust & Huang, 2021). Considering these, consumers'

weakened resistance against AI work may not obviously apply to some functional apparel products that are related to physical as well as symbolic wellness. In any case, from the results of Study 1 that compared self-expressive and functional products in the same product category (i.e., jacket), it is suggested that consumer responses to human-designed apparel products are more favorable for both self-expressive and functional products. The mediation effects of perceived experience and agency are found to be similar for both products.

Lastly, Study 1 examined the moderation of perceived threats from AI. It was hypothesized that consumers with lower perceived threats from AI would react less negatively against AI-designed fashion products than those with higher perceived threats (H5a). The results showed that the preference for human-designed over AI-designed jackets holds across the different levels of perceived threats. Participants liked the product and the brand more and were more willing to purchase the human-designed (vs. AI-designed) jacket regardless of perceived threats from AI. As a recent McKinsey article commented (Harreis et al., 2023), it may be because the use of generative AI in the fashion design process is relatively nascent compared to other AI-assisted services. Psychologists have stated that humans first exhibit a strong aversion to novel stimuli due to less perceived safety and less familiarity (Berlyne, 1970). Considering that, Study 1 participants may have shown negative responses to AI-designed jackets because it is seen as a rather newfangled technology, regardless of perceived threats from AI.

In contradiction, the moderation of perceived threats from AI on the serial mediation of mind perception and perceived design expertise was found to be significant for product attitude. It was hypothesized that the mediation would be strengthened (vs.

weakened) if consumers feel more (vs. less) intimidated by AI (H5b). The differences in the product attitude of AI-designed and human-designed jackets due to mind perception and perceived design expertise were amplified for consumers with higher perceived threats from AI (see Table 15). The reason underlying higher product attitude toward human-designed products, which is humans' higher mind perception and perceived design expertise, plays the explaining role more strongly for consumers with higher AI threats. However, such a pattern was not found for purchase intention and brand attitude. These results may be because the mediating effects of mind perception and perceived design expertise may not have significant positive association with perceived AI threats in the case of purchase intention and brand attitude. Compared to product attitude which is more directly affected by the perception of design entity and immediately formed, purchase intention and brand attitude may not be directly affected because they are more multi-faceted factors or formed over time (Ajzen & Fishbein, 1977; Gardner, 1985; Mitchell, 1986). Thus, the levels of mediation may not have significantly differed depending on the perceived threats from AI regarding purchase intention and brand attitude.

Chapter 5. Study 2

Chapter 5 presents the Study 2 methods, results, and discussion. After the study design, procedure, and measurement are described, preliminary data analysis and hypothesis testing is presented. The findings of Study 2 are discussed at the end.

5.1 Methods

The purposes of Study 2 were twofold. First, Study 2 aimed to replicate the findings of Study 1 about the effect of design entity (AI vs. human) on consumer responses and mind perception (H1, H2a) and mediation of mind perception and perceived design expertise (H2b, H3). Second, Study 2 tested whether consumers' negative responses to AI-designed products would be weaker when human aspects are incorporated into AI applications (H6). It was hypothesized that consumers' negative responses to AI-designed fashion products would be the weakest when the products are described to be designed through human-AI collaboration, followed by Humanized AI designer and AI.

5.1.1 Study Design and Participants

A one-factor four-level (design process: AI vs. humanized AI designer vs. human-AI collaboration vs. human) between-subject online experiment was conducted. Human aspects incorporated into the design process were manipulated using short product descriptions under the product image. The number of participants for recruitment was determined based on an a priori power analysis using G*Power 3.1 (Faul et al., 2009) and the literature on the sample size (Sim et al., 2022). The power analysis showed that at least a sample size of 187 is needed for MANOVA to detect the effect size Cohen's f^2

of .03 with α of .05 and a power of .80 (Cohen, 1992). The effect size was computed using the pilot study's Pillai's trace (V=.09) and the number of potential predictors (1 independent variable and 3 covariates) and response variables (6 dependent variables). The Pillai's trace was adopted from the pilot study because the Pillai's trace value from the pilot study (.09) was smaller than the value from Study 1 (.82). The suggested minimum sample size from the literature on the number of mediators and sample size was 160 (Sim et al., 2022). Thus, 300 adults living in the U.S. and fluent in English were recruited through Prolific to ensure a sufficient sample size after careless response detection and data cleaning. Those who participated in Pretest 2, Pretest 3, and Study 1 on Prolific were excluded from the study (see 5.1.2 for details of Pretest 3).

Multiple attention check questions that are similar to those used in Study 1 were included to detect careless responses and ensure quality data (Curran, 2016). One participant was excluded because the participant selected the same response (7) to all scale items. Ten participants were dropped because they failed more than one attention check question. Thus, 289 participants remained in the final sample (M_{age}=35.73, SD_{age}=12.42). Table 17 shows Study 2 participant characteristics.

Table 17

Participant Characteristics (Study 2)

Characteristics		**N**	**Percent**
Gender	Male	164	56.75%
	Female	121	41.87%
	Other; prefer not to answer	4	1.38%
Ethnicity	American Indian or Alaska native	3	1.04%
	Middle Eastern and North African	3	1.04%
	Native Hawaiian or other Pacific Islander	2	0.69%
	White / Caucasian	197	68.17%

	Hispanic or Latino	26	9.00%
	Asian	25	8.65%
	Black, African, African American	23	7.96%
	Other	10	3.46%
Income	Less than $25,000	66	22.84%
	$25,000 - $49,999	80	27.68%
	$50,000 - $74,999	57	19.72%
	$75,000 - $99,999	42	14.53%
	$100,000 or more	44	15.22%
Education *(highest degree received)*	Elementary school	4	1.38%
	High school or equivalent (e.g., GED)	49	16.96%
	Some college, but no degree	71	24.57%
	Associate's degree	19	6.57%
	Bachelor's degree	107	37.02%
	Master's degree	29	10.03%
	Professional degree	4	1.38%
	Doctoral degree	5	1.73%
	Other	1	0.35%
Marital status	Married	96	33.22%
	Single	166	57.44%
	Divorced	13	4.50%
	Separated	3	1.04%
	Widowed	2	0.69%
	Other; prefer not to answer	9	3.11%
Job situation	Full-time	148	51.21%
	Part-time	58	20.07%
	Unemployed	55	19.03%
	Retired	11	3.81%
	Other; Prefer not to answer	17	5.88%
Total			**289**

5.1.2 Pretests and Stimuli

Short product descriptions and a sweater image were used as stimuli. Product descriptions were used to manipulate the design process in line with the suggestions from the literature (e.g., Hong, 2018; Zhang et al., 2022). The sweater image was identical across the study conditions, whereas the product descriptions differed. Participants were given an image of a sweater from a fictitious brand Knizzaz. They were told that the

sweater was designed either by AI, by AI designer 'Vella,' through human-AI collaboration, or by human designers. The stimuli were developed through multiple pretests (Pretests 1, 2, and 3). The fictitious brand name was selected based on Pretest 1. Pretest 2 (n=99; M_{age}=35.46, SD_{age}=12.14; Prolific) aimed to check the manipulation of Study 1 scenarios and develop appropriate stimuli for Study 2. The details of Pretest 1 and Study 1 part of Pretest 2 are presented in 4.1.2.

For Study 2, Pretest 2 aimed to select the most appropriate product image and the name of the humanized AI designer. Participants viewed five product images and rated each product. After that, they viewed and rated four fictitious names. The five product images were created by an AI program Midjourney[16] that allowed the use of images upon paid services. The four fictitious names for an AI designer were created using a fake name generator web service. Product attitudes were measured on a 7-point semantic scale (Chae & Hoegg, 2013): *bad – good*, *dislikable – likable*, *negative – positive*, and *unappealing – appealing.* Attitudes toward the names were measured using a 7-point semantic scale: *bad – good*, *dislikable – likable*, and *negative – positive.* The scales showed good internal reliability for all five product images (α>.95) and four names (α>.94). A sweater image and the name *Vella* were selected because participants did not show strong preference or dislike them compared to other options (sweater: *M*=4.08, *SD*=1.38; Vella: *M*=4.06, *SD*=1.30). This approach was adopted to avoid potential confounding effects of strong opinions toward the product image or the AI designer's name.

[16] https://www.midjourney.com/

Pretest 3 (n=97, M_{age}=36.15, SD_{age}=12.66; Prolific) aimed to check the manipulation of human aspects incorporated into the AI applications in Study 2 product descriptions. Participants were randomly assigned to one of the three conditions. They viewed the sweater image that was described to be designed either by AI, by AI designer 'Vella,' or through human-AI collaboration, and indicated their opinions about the design process. The human aspects in AI applications were checked with a single 10-point semantic scale item modified from the scale of Choi et al.'s (2021) study. Participants were asked to indicate the extent to which the product design process was more like by AI or humans: *0 = Mostly by AI. The product was designed through an algorithm's automated processes*; *5 = By an equal combination of an algorithm's automation and human design processes*; and *10 = Mostly by humans. The product was designed through human design processes*.

The results of Pretest 3 showed successful manipulation of human aspects in AI applications, indicating the appropriateness of the scenarios for Study 2. Perceived design process was significantly different between the conditions ($F(2, 94)=50.03$, $p<.001$, partial $\eta^2=.52$). Participants in the human-AI collaboration condition perceived the highest human intervention (M_{collab}=4.22). Participants in the AI condition and the humanized AI designer condition perceived the least human intervention (M_{AI}=0.73, $M_{AI\ designer}$=0.75), indicating that the differences in perceived human intervention in the design process between AI and AI designer conditions were non-significant. Considering the industry trend of naming AI agents (Smith, 2022; Ting, 2022), any of the AI and AI designer conditions was not omitted. Figure 8 shows the sweater image and product descriptions used in Study 2.

Figure 8

Study 2 Stimuli

Note. "by Artificial Intelligence (AI)" were replaced either by "by AI designer 'Vella'," "through human-AI collaboration," or "by human designers" depending on the study conditions.

5.1.3 Procedure

Participants voluntarily participated in the study by clicking the survey link on Prolific, reading an IRB-approved consent form, and indicating their agreement to take the survey. After answering the qualification questions (i.e., living in the U.S., 18 years old or older), participants were randomly assigned to one of the four conditions. They viewed a short product description and a sweater image (see 5.1.2) and completed the questionnaire. The questionnaire showed the manipulation check questions, the questions measuring the variables about design process, product, brand, and covariates, and attention check questions. Participants provided demographic information at the end of the questionnaire. Each participant received $1.60 as an incentive upon completion.

5.1.4 Measurements

The same measurements as those used in Study 1 were used for mind perception of experience and agency (Gray et al., 2007), design expertise (Ratneshwar & Chaiken, 1991; Schreier et al., 2012), product attitude (Chae & Hoegg, 2013), purchase intention (Schlosser et al., 2006), and brand attitude (Mitchell & Olson, 1981). The questions for measuring mind perception and design expertise were edited based on the study condition. For example, "How much is AI capable of the following?" in the AI condition was changed to "how much are the entities working for human-AI collaboration capable of the following?" in the human-AI collaboration condition. The covariates were also measured using the same scales used in Study 1: familiarity with AI services (Belanche et al., 2019), experience in product design (Page & Uncles, 2014), and fashion involvement (O'cass, 2004). The measurement items are presented in Table 6.

Perceived human intervention in the design process was checked using a single slider scale where participants indicated the extent to which the product design process was more like by AI or humans. Participants could use a slider to indicate from 0 at minimum to 100 at maximum. The higher (vs. lower) the slider value indicates that participants thought the design process seemed more like mostly by humans (vs. AI).

5.2 Results

5.2.1 Preliminary Data Analysis

Exploratory Factor Analysis. Exploratory factor analysis (EFA) was first performed on the fifty-three items to understand the latent structure underlying the items (Zhang et al., 2020) better and refine the measurements. Principal component analysis

(PCA) estimation and oblique factor rotation method with direct oblimin criterion were used as it is the common method when some factor correlation values exceed .32 (Tabachnick & Fidell, 2007). A scree plot was plotted to display the eigenvalue explained by each component. The elbow of a scree plot that displays the eigenvalue explained by each component was used, resulting in nine factors. The factors with low factor loadings (<.04) were removed (Child, 2006).

The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy (.94) confirmed the appropriateness of the data sample size. The Bartlett's Test of Sphericity (χ^2 (n=288) = 22638.38, p<.001) showed significant correlations among some of its components, indicating suitability for factor analysis. The nine factors accounted for 87.46% of the total variance. Most items were loaded on the desired factor consistent with the existing scales. The same item from perceived agency as excluded in Study 1 (Magen_3) was removed because it was loaded on perceived experience, not perceived agency. The items cross-loaded on two or more factors were marked for further examination. The results of EFA after removing one item are shown in Table 18.

Table 18

Results of Exploratory Factor Analysis (Study 2)

Items	Components								
	1	2	3	4	5	6	7	8	9
Mexp_7	**.99**	-.04	.04	-.01	.04	.07	.01	-.04	-.06
Mexp_4	**.98**	.00	.03	-.01	-.02	.05	.03	-.04	-.07
Mexp_5	**.98**	-.03	.05	.01	.03	.07	.02	-.05	-.07
Mexp_9	**.98**	.00	.00	.00	-.01	.04	-.03	.02	-.04
Mexp_3	**.97**	.02	.00	-.01	-.01	.01	-.01	.00	.01
Mexp_2	**.97**	.01	-.01	.02	.00	-.02	-.01	.03	.02
Mexp_11	**.95**	-.02	.00	-.05	.00	.01	.01	-.01	-.06
Mexp_6	**.94**	.01	.02	.00	.00	-.02	-.02	.01	-.05
Mexp_10	**.94**	.00	-.03	-.01	.02	-.07	-.01	.05	.03

Mexp_8	**.82**	.02	.04	.06	-.03	-.19	.02	.11	.08
Mexp_1	**.76**	.06	-.03	.05	-.03	-.26	.03	.13	.06
Magen_1	**.50**	.06	.03	-.04	.03	**-.40**	-.05	-.04	-.13
FasInV_7	-.04	**.95**	.08	.01	-.03	-.08	.06	-.03	.07
FasInV_14	-.05	**.95**	.00	-.02	.00	-.06	.03	.02	-.05
FasInV_8	.11	**.94**	.01	.03	-.03	.09	.02	-.02	.04
FasInV_1	.03	**.94**	-.06	.01	-.01	.03	-.06	-.01	-.01
FasInV_13	.02	**.93**	.11	.03	-.02	-.03	.10	-.01	.04
FasInV_5	-.07	**.93**	.00	.04	-.02	-.06	.02	.00	.01
FasInV_11	-.03	**.92**	-.01	-.03	.02	-.08	.06	.04	-.03
FasInV_2	-.04	**.91**	-.04	-.01	-.01	.02	-.03	.05	-.03
FasInV_3	.02	**.89**	-.05	-.02	.02	.11	-.07	-.03	-.05
FasInV_4	.02	**.89**	.04	.02	.05	.01	-.03	-.06	.02
FasInV_12	.07	**.89**	-.07	-.03	.06	.04	-.02	.05	.02
FasInV_6	-.08	**.88**	.05	-.02	.07	-.12	.03	.02	.04
FasInV_9	.03	**.88**	.00	.01	.04	.11	-.04	-.02	-.03
FasInV_10	.02	**.84**	-.06	-.03	.01	.07	-.14	-.01	-.07
ProAtt_5	.00	.01	**.93**	-.01	-.02	-.03	-.10	-.06	.00
ProAtt_3	.03	-.01	**.92**	-.04	.03	.02	-.05	.03	.02
ProAtt_2	.01	.00	**.90**	.03	-.03	.00	-.06	.00	-.03
ProAtt_1	.04	.01	**.87**	.02	-.03	.01	.04	.10	-.03
ProAtt_4	-.01	.00	**.87**	.00	.03	.01	.00	.07	-.05
FamAI_2	.04	.01	-.01	**.93**	.04	.04	.01	-.01	-.02
FamAI_1	-.01	-.03	-.02	**.91**	-.07	.05	-.07	-.03	-.08
FamAI_3	-.02	.01	.01	**.85**	.04	-.07	.04	.03	.07
ExpDes_1	.01	.01	-.03	-.01	**.96**	-.01	-.05	.05	.03
ExpDes_3	.00	.01	-.01	.00	**.96**	-.03	.04	-.01	.00
ExpDes_2	.02	.01	.02	.03	**.95**	.02	-.02	-.05	-.02
Magen_2	-.16	-.02	.07	.06	.03	**-.84**	.09	.04	-.17
Magen_5	.16	-.02	.08	.01	-.01	**-.74**	.01	-.04	-.07
Magen_4	.21	.03	-.10	.01	-.06	**-.74**	-.09	.04	-.01
Magen_7	**.41**	-.01	.03	.01	.01	**-.58**	-.10	.00	.01
Magen_6	.32	.03	-.10	-.01	-.07	**-.48**	-.28	-.10	-.17
PI_3	-.05	.00	.06	.01	.04	.01	**-.92**	.05	-.01
PI_2	-.04	.00	.12	.03	.02	-.01	**-.88**	.05	.02
PI_1	-.04	.04	.08	-.01	.01	-.01	**-.88**	.09	.01
BraAtt_1	.00	.02	-.01	.03	-.02	-.01	-.01	**.95**	-.01
BraAtt_3	.00	.02	.05	.00	-.01	-.02	.00	**.91**	-.04
BraAtt_4	.01	-.02	-.01	.00	-.01	.06	-.09	**.91**	-.02
BraAtt_2	.03	-.04	.08	-.02	.02	.01	-.01	**.88**	-.04
DesExp_3	.00	.01	.04	.05	-.03	-.03	.02	.04	**-.89**
DesExp_2	-.07	-.01	.06	.06	-.01	-.11	.03	.05	**-.88**
DesExp_1	.21	.01	.04	-.07	.03	.04	-.06	.09	**-.73**
Eigenvalue	15.77	12.02	7.60	2.83	2.31	1.51	1.33	1.15	0.96
% of Variance Extracted	30.33	23.11	14.62	5.44	4.43	2.90	2.56	2.21	1.86

Note. Bold numbers are the factor loadings higher than .40.

Cronbach's Alpha. The Cronbach's alpha value for each construct with the final measurement items (see also Confirmatory Factor Analysis below) was computed to ensure the construct validity and internal consistency. All alpha values were larger than the generally accepted value of .70, indicating good construct validity and reliability (Cortina, 1993). Table 19 shows the results of EFA with the final measurements and the Cronbach's alpha values.

Table 19

Results of Exploratory Factor Analysis with Final Items (Study 2)

Items	Components								
	1	2	3	4	5	6	7	8	9
Mexp_7	**.99**	-.04	.03	-.01	.04	.00	.06	-.04	-.05
Mexp_5	**.99**	-.03	.05	.01	.02	-.01	.06	-.05	-.06
Mexp_4	**.98**	.01	.03	-.01	-.02	-.03	.04	-.04	-.06
Mexp_9	**.97**	.00	.00	.00	-.01	.03	.02	.02	-.03
Mexp_3	**.97**	.02	-.01	-.02	-.02	.01	-.01	.00	.02
Mexp_2	**.96**	.01	-.01	.02	-.01	.01	-.05	.03	.03
Mexp_11	**.95**	-.01	.00	-.05	-.01	.00	.00	-.01	-.05
Mexp_6	**.93**	.01	.02	.00	.00	.02	-.04	.01	-.04
Mexp_10	**.91**	.00	-.03	-.01	.02	.01	-.10	.05	.04
Mexp_8	**.78**	.02	.04	.06	-.03	-.03	-.22	.11	.08
Mexp_1	**.71**	.06	-.02	.05	-.02	-.04	-.30	.13	.05
FasInV_7	-.06	**.95**	.08	.01	-.02	-.07	-.09	-.02	.06
FasInV_14	-.06	**.94**	.00	-.02	.00	-.03	-.07	.02	-.05
FasInV_8	.12	**.94**	.01	.02	-.03	-.01	.10	-.02	.05
FasInV_1	.05	**.94**	-.06	.01	-.02	.06	.05	-.02	-.01
FasInV_13	-.01	**.93**	.12	.03	-.02	-.10	-.05	-.01	.04
FasInV_5	-.08	**.93**	.00	.04	-.01	-.02	-.07	.01	.00
FasInV_11	-.04	**.91**	-.01	-.02	.02	-.06	-.08	.04	-.03
FasInV_2	-.04	**.90**	-.04	-.02	-.01	.03	.01	.05	-.03
FasInV_3	.05	**.90**	-.05	-.02	.02	.08	.12	-.03	-.05
FasInV_4	.02	**.89**	.04	.02	.06	.03	.00	-.06	.02
FasInV_12	.08	**.89**	-.07	-.03	.06	.03	.05	.05	.02
FasInV_9	.06	**.88**	-.01	.01	.04	.05	.14	-.02	-.02
FasInV_6	-.10	**.88**	.05	-.02	.07	-.04	-.13	.02	.03
FasInV_10	.04	**.85**	-.06	-.03	.01	.15	.08	-.02	-.07
ProAtt_5	-.01	.01	**.93**	-.01	-.02	.10	-.03	-.06	-.01
ProAtt_3	.04	-.01	**.92**	-.04	.02	.05	.03	.03	.02
ProAtt_2	.01	.00	**.90**	.03	-.03	.05	.01	.00	-.03

ProAtt_1	.04	.01	**.87**	.02	-.03	-.04	.02	.10	-.03
ProAtt_4	-.01	.00	**.86**	.00	.03	.00	.02	.07	-.05
FamAI_2	.04	.01	-.01	**.93**	.04	-.01	.03	.00	-.02
FamAI_1	.02	-.03	-.02	**.92**	-.07	.08	.08	-.03	-.08
FamAI_3	-.05	.01	.02	**.85**	.05	-.05	-.09	.03	.06
ExpDes_1	.00	.01	-.03	-.01	**.96**	.04	-.01	.05	.03
ExpDes_3	-.01	.01	-.01	.00	**.96**	-.04	-.02	.00	-.01
ExpDes_2	.02	.01	.02	.03	**.95**	.02	.03	-.05	-.03
PI_3	-.04	.00	.05	.01	.04	**.92**	-.03	.04	.00
PI_2	-.02	.00	.11	.03	.02	**.89**	-.03	.04	.03
PI_1	-.03	.04	.07	-.01	.01	**.88**	-.03	.08	.02
Magen_4	.07	.02	-.08	.01	-.04	.04	**-.82**	.05	-.05
Magen_5	.04	-.03	.09	.02	.01	-.05	**-.79**	-.03	-.12
Magen_7	.29	-.02	.05	.01	.02	.06	**-.66**	.01	-.02
Magen_6	.21	.03	-.08	.00	-.06	.24	**-.58**	-.09	-.19
Magen_1	**.42**	.06	.04	-.03	.04	.02	**-.46**	-.03	-.14
BraAtt_1	-.01	.02	-.01	.03	-.02	.01	-.01	**.95**	-.01
BraAtt_3	-.01	.02	.05	.00	-.01	-.01	-.01	**.91**	-.04
BraAtt_4	.02	-.01	-.01	.00	-.01	.10	.08	**.91**	-.02
BraAtt_2	.02	-.04	.08	-.02	.02	.01	.01	**.88**	-.04
DesExp_3	-.02	.01	.05	.05	-.03	-.03	-.03	.04	**-.90**
DesExp_2	-.10	-.01	.06	.06	-.01	-.04	-.11	.05	**-.89**
DesExp_1	.22	.01	.04	-.07	.03	.06	.04	.09	**-.73**
Eigenvalue	15.58	11.96	7.60	2.67	2.29	1.40	1.25	1.14	0.94
% of Variance Extracted	30.56	23.45	14.90	5.24	4.48	2.74	2.45	2.23	1.84
Cronbach's α	.99	.98	.97	.88	.96	.97	.92	.97	.91

Note. Bold numbers are the factor loadings higher than .40.

Confirmatory Factor Analysis. Confirmatory factor analysis (CFA) was performed to confirm the a priori relationship between the observed variables and the latent factors (Chen et al., 2020). Maximum-likelihood estimation method and AMOS 29 were used. Regression imputation was performed for two missing values in the data (Harrington, 2009). The measurement model showed an adequate fit, but the same item from perceived agency excluded as in Study 1 (Magen_2) was removed since it showed a low standardized loading (.60) to its latent variable. The final model fit indices showed a good fit (χ^2=1909.05, *df*=1146; χ^2/df=1.67; CFI=.97; NNFI=.96; RMSEA=.05;

SRMR=.04). The widely accepted index thresholds were applied was used to assess the model fit (see 4.2.1 for details).

The convergent validity of the constructs was supported. First, the composite reliabilities for all constructs were larger than .70. Second, the items of each scale were loaded on its construct with significant loadings (p<.001; see Table 20). Lastly, the average variance extracted (AVE) for each construct exceeded the benchmark of .50 (Hair et al., 2019). The discriminant validity of the constructs was supported since the variance extracted for all constructs was larger than the squared correlation of variables (Fornell & Larcker, 1981). Table 21 shows the descriptive statistics, AVE, correlations, squared correlations, and composite reliabilities of the latent factors.

Similar to Study 1, the correlation between perceived experience and agency was high (.82). The author used the two constructs separately because of the high loadings between the two stated in the literature and the appropriate degree to which measures of experience and agency are distinct (see 4.2.1 and Table 21). Additionally, the index of mind perception (α=.98) was used by averaging the indices of perceived experience and agency and used in the additional analyses.

Table 20

Confirmatory Factor Analysis: Standardized Factor Loadings (Study 2)

Construct	Item	Loading	Construct	Item	Loading
Mind perception of Experience	Mexp_1	.88		PI_3	.96
	Mexp_2	.98	Brand attitude	BraAtt_1	.94
	Mexp_3	.96		BraAtt_2	.94
	Mexp_4	.98		BraAtt_3	.95
	Mexp_5	.96		BraAtt_4	.94
	Mexp_6	.99		FamAI_1	.87

	Mexp_7	.97	Familiarity with AI services	FamAI_2	.92
	Mexp_8	.89		FamAI_3	.74
	Mexp_9	.98	Experience in product design	ExpDes_1	.97
	Mexp_10	.96		ExpDes_2	.95
	Mexp_11	.96		ExpDes_3	.92
Mind perception of Agency	Magen_1	.86	Fashion involvement	FasInV_1	.94
	Magen_4	.80		FasInV_2	.89
	Magen_5	.79		FasInV_3	.90
	Magen_6	.82		FasInV_4	.91
	Magen_7	.87		FasInV_5	.89
Perceived design expertise	DesExp_1	.79		FasInV_6	.89
	DesExp_2	.94		FasInV_7	.92
	DesExp_3	.94		FasInV_8	.92
Product attitude	ProAtt_1	.92		FasInV_9	.89
	ProAtt_2	.94		FasInV_10	.87
	ProAtt_3	.94		FasInV_11	.91
	ProAtt_4	.93		FasInV_12	.92
	ProAtt_5	.94		FasInV_13	.88
Purchase intention	PI_1	.96		FasInV_14	.94
	PI_2	.95			Total: 51 items

Common Method Bias. The presence of common method bias was tested using Harman's one-factor test. The total variance extracted by one factor using the final 51 items was 30.56%, which is less than the recommended threshold of 50% (Podsakoff & Organ, 1986). Thus, common method bias was not a major concern in this study.

Table 21

AVE, Factor Correlations, and Composite Reliabilities (Study 2)

Construct	1	2	3	4	5	6	7	8	9
1. Mind perception of Experience	**.91**	.68	.21	.04	.04	.03	.00	.00	.01
2. Mind perception of Agency	.82	**.69**	.33	.05	.05	.04	.01	.00	.01
3. Perceived design expertise	.46	.58	**.79**	.27	.08	.25	.07	.01	.00
4. Product attitude	.19	.23	.52	**.87**	.41	.54	.02	.00	.00
5. Purchase intention	.21	.22	.28	.64	**.92**	.34	.00	.03	.05
6. Brand attitude	.18	.21	.50	.73	.59	**.88**	.01	.00	.01
7. Familiarity with AI services	.01	.11	.26	.13	.02	.11	**.72**	.00	.00
8. Experience in product design	-.03	-.04	-.10	-.04	.18	-.02	.05	**.89**	.20
9. Fashion involvement	.10	.11	.02	.03	.22	.08	-.04	.45	**.82**
Mean	3.16	4.37	5.04	4.66	2.71	4.31	5.21	2.77	2.95
SD	2.37	1.90	1.42	1.48	1.52	1.11	1.22	1.57	1.58
Composite Reliability[a]	.99	.92	.92	.97	.97	.97	.89	.96	.98

Note. Average variance extracted[b] (AVE) values are bold numbers on the diagonal axis. Values below the diagonal are correlations. Values above the diagonal are squared correlations.

[a] Composite Reliability = $(\sum \text{standardized loading})^2 / (\sum \text{standardized loading})^2 + \sum \text{measurement error}$

[b] Variance Extracted = $\sum (\text{standardized loading})^2 / \sum (\text{standardized loading})^2 + \sum \text{measurement error}$

5.2.2 Hypothesis Testing

Manipulation Check. Perceived human intervention in the design process between the four conditions (AI vs. humanized AI designer vs. human-AI collaboration vs. human) was significantly different ($F(3, 285)=32.04$, $p<.001$, partial $\eta^2=.25$). Participants in the human condition perceived the design process as being mostly by humans (vs. computers) the most ($M_{human}=73.15$), followed by those in the human-AI collaboration condition ($M_{collab}=42.96$), the AI condition ($M_{AI}=36.90$), and the humanized AI designer condition ($M_{AI\ designer}=36.76$). Perceived human intervention in the human condition was significantly higher than those in the AI ($p<.001$), humanized AI designer ($p<.001$), and human-AI collaboration ($p<.001$) conditions. Perceived human intervention in the human-AI collaboration was marginally higher than those in the AI ($p=.051$) and humanized AI designer ($p=.061$) conditions. Lastly, participants perceived similar levels of human intervention from the AI and humanized AI designer ($p=.488$).

Covariates and Assumption Check. MANCOVA was performed to test the differences in consumer responses, mind perception, and perceived design expertise depending on the design process (AI vs. humanized AI designer vs. human-AI collaboration vs. human). Design process was entered as an independent variable, and perceived experience, perceived agency, perceived design expertise, product attitude, purchase intention, and brand attitude were entered as dependent variables. The potential covariates were age, gender, familiarity with AI, experience in design, and fashion involvement. All potential covariates showed a significant correlation with at least one dependent variable at a significance level of .05. Unlike Study 1, gender ($p=.014$) and experience in product design ($p=.009$) in addition to familiarity with AI services

(p<.001) and fashion involvement (p=.004) showed significant effects on the dependent variables. Although age showed a marginal effect (p=.060) on the dependent variables in the multivariate analysis, age was also included as the covariate to rule out potential confounding effect. Therefore, the five variables were entered as covariates. The post hoc power analysis with five covariates showed adequate power (.88).

The assumptions of MANOVA and ANOVA were checked. First, the correlations between the dependent variables were moderately high and did not exceed .90 (see Table 21), indicating that performing MANOVA is appropriate. Second, the Box's M test showed a significant difference in covariances (p<.001), indicating the violation of the MANOVA assumption of the equality of variance-covariance matrices. Thus, Pillai's trace criterion was used instead of Wilk's lambda criterion because MANOVA and Pillai's trace are robust against heterogeneity of covariances in large balanced sample sizes (Bray & Maxwell, 1985; Tabachnick & Fidell, 2007).

Lastly, the homogeneity of variance assumption of ANOVA was checked by looking at Levene's test of equality of error variances, since the results of the subsequent univariate analyses are used in case of significant multivariate results. The assumption was met for product attitude (p=.209), purchase intention (p=.084), and brand attitude (p=.251). However, the variances of perceived experience (p<.001), agency (p<.001), and design expertise (p<.001) significantly differed across groups. The ratios of the largest to smallest variances of the four study conditions were computed to further test the appropriateness (see Table 22). Four was used as a criterion given that ANOVA on balanced data is robust in the heterogeneity of variance if the ratio of the largest to smallest group variances is not larger than 4 (Dean & Voss, 1999; Kurilla, 2015). The

ratios for perceived design expertise, product attitude, purchase intention, and brand attitude showed the appropriateness of interpreting ANOVA results. However, the ratios for perceived experience and agency were larger than 4. Thus, perceived experience and agency were excluded from interpreting ANOVA results. Instead, a separate Welch's ANOVA was performed for perceived experience and agency because Welch's F-test examines the equality of means of more than two groups when the homogeneity of variance assumption is not met (Field, 2013). Although Welch's ANOVA does not adjust means based on covariates, performing Welch's ANOVA without covariates for perceived experience and agency was appropriate because the covariates were not significantly correlated with perceived experience and agency but only with other dependent variables. The correlations between the covariates and perceived experience and agency are presented in Table 23.

Table 22

Ratio of the Largest to Smallest Group Variances (Study 2)

	Perceived experience	Perceived agency	Perceived design expertise	Product attitude	Purchase intention	Brand attitude
s^2_{max}/s^2_{min}	6.91	7.75	3.76	1.74	1.86	2.03

Table 23

Correlations between Covariates and Perceived Experience and Agency

	Perceived Experience	Perceived Agency
Age	$.03^{ns}$	$.00^{ns}$
Gender	$-.05^{ns}$	$-.10^{ns}$
Familiarity with AI	$.01^{ns}$	$.11^{ns}$
Fashion Involvement	$.09^{ns}$	$.10^{ns}$
Experience in Design	$-.03^{ns}$	$-.05^{ns}$

Effect of Design Process and Human Aspects. The results of multivariate tests showed a significant main effect of design process (Pillai's V=.86, p<.001, partial η^2=.29), controlling for age, gender, familiarity with AI, fashion involvement, and experience in design. To rule out possible Type I error (false-positive), another MANCOVA was performed excluding perceived experience and agency. The results also showed a significant main effect of design process (Pillai's V=.30, p<.001, partial η^2=.10). The subsequent between-subject effects analysis controlling for the covariates showed significant differences between the four conditions in perceived design experience (F(3, 280)=33.40, p<.001, partial η^2=.26), product attitude (F(3, 280)=4.31, p=.005, partial η^2=.04), and brand attitude (F(3, 280)=2.65, p=.049, partial η^2=.03). The differences in purchase intention (F(3, 280)=2.27, p=.081, partial η^2=.02) were marginally (non)significant. Welch's ANOVA was performed to see the differences in perceived experience and agency. The significant differences between the conditions in perceived experience (Welch's F(3, 152.97)= 913.77, p<.001) and agency (Welch's F(3, 141.04)=186.18, p<.001) were found.

Post hoc pairwise comparisons were performed to test the hypotheses by comparing the participants' responses between the four conditions (design process: AI vs. humanized AI designer vs. human-AI collaboration vs. human). The results of the pairwise comparisons are presented in Figure 9 and Appendix C. First, the AI and human conditions were compared to examine the effect of design entity (AI vs. human) on consumer responses (H1) and mind perception (H2a). Multiple pairwise comparisons using Bonferroni correction controlling for the five covariates were performed on perceived design expertise, product attitude, purchase intention, and brand attitude.

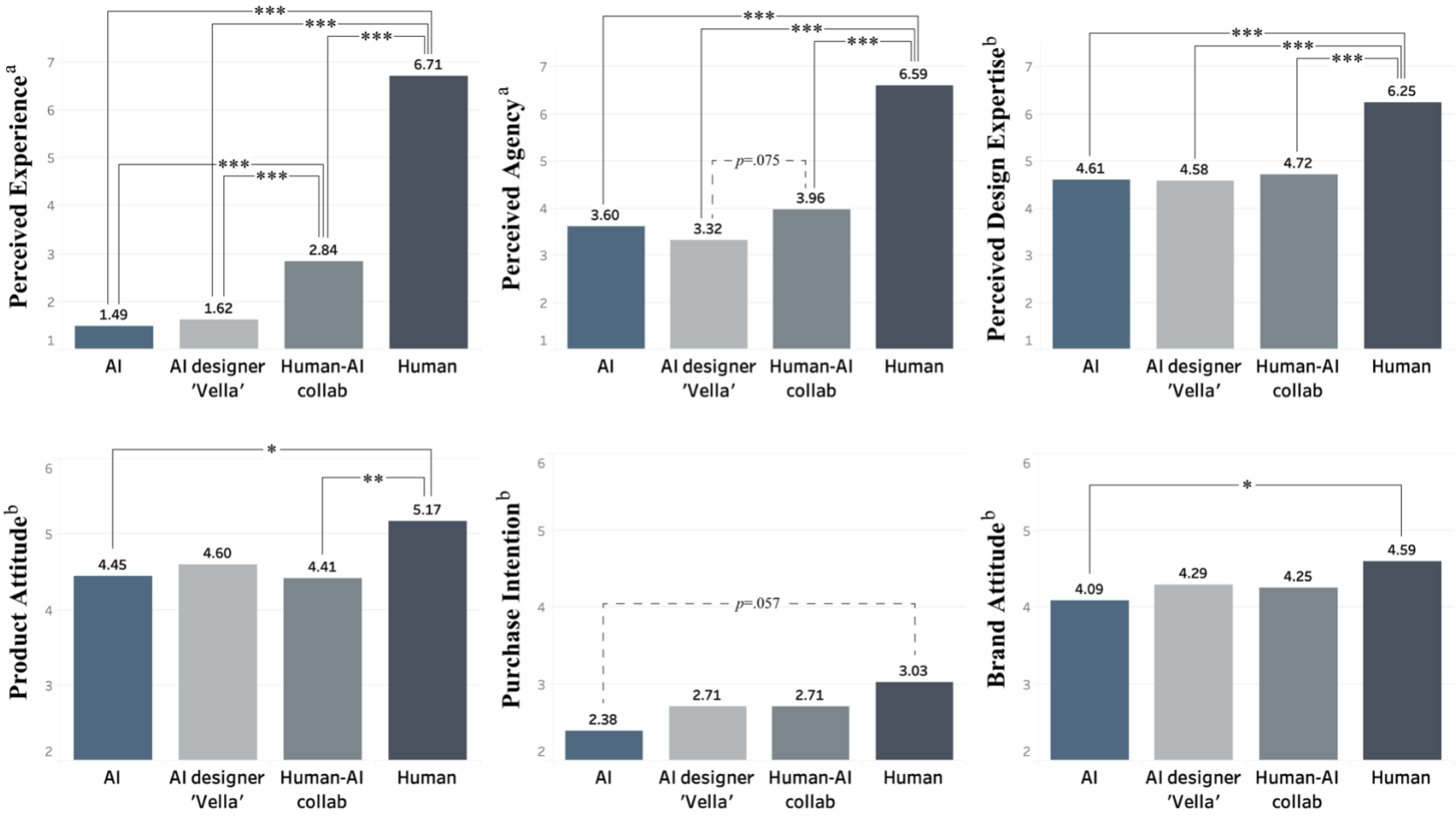
Participants in the human (vs. AI) condition perceived higher design expertise (M_{AI}=4.61 vs. M_{human}=6.25, p<.001). They also formed higher positive product attitude (M_{AI}=4.45 vs. M_{human}=5.17, p=.018) and brand attitude (M_{AI}=4.09 vs. M_{human}=4.59, p=.038) and marginally higher purchase intention (M_{AI}=2.38 vs. M_{human}=3.03, p=.057). Games-Howell post hoc tests were performed on perceived experience and agency because Games-Howell test does not require the groups to have equal variances. Participants in the human condition perceived higher experience (M_{AI}=1.49 vs. M_{human}=6.71, p<.001) and agency (M_{AI}=3.60 vs. M_{human}=6.59, p<.001) than in those in the AI condition. Thus, H1 and H2a were again supported.

Next, the four conditions were compared to examine the moderation of the level of incorporating human aspects into AI in the design process (H6; see Figure 9 and Appendix C). The results of Bonferroni pairwise comparisons controlling for the five covariates showed significant differences in perceived design expertise between the human condition and the other three conditions (all p<.001). That is, participants perceived the highest design expertise from the entities in the design process when the sweater was described to be designed by human, but the responses did not differ between the AI, AI designer, and human-AI collaboration. Product attitude in the human condition was significantly different from the AI (p=.018) and human-AI collaboration (p=.010) conditions. The superiority of human-designed sweater on product attitude was not shown compared to the sweater designed by AI designer. Significant differences in purchase intention (p=.057) and brand attitude (p=.038) were found between the human and AI conditions, but the AI designer and human-AI collaboration conditions did not show significant differences from any conditions. These results mean that participants

were more willing to purchase and form more favorable brand attitudes in response to the human-designed sweater than the AI-designed sweater. In contrast, the advantages of the human-designed sweater regarding purchase intention and brand attitude were not shown compared to the sweater designed by an AI designer 'Vella' or through human-AI collaboration. Lastly, the results of Games-Howell post hoc tests showed that participants in the human condition perceived significantly higher experience and agency than those in the other three conditions (all $p<.001$). The entities working for human-AI collaboration were perceived to have significantly higher experience than AI ($p<.001$) and AI designer 'Vella' ($p<.001$) and marginally higher agency than AI designer 'Vella' ($p=.075$). H6 posited that the negative responses to AI-designed products would be the weakest when the products are described to be designed through human-AI collaboration, followed by Humanized AI designer and AI. This pattern was shown for perceived experience, but not for the remaining five dependent variables. Thus, H6 was not supported.

Figure 9

Post Hoc Pairwise Comparisons: Effect of Design Process



Note. Asterisks indicate significance level: * $p<.05$, ** $p<.01$, *** $p<.001$; [a]Games-Howell post hoc test; [b]Bonferroni post hoc test.

Mediation of Mind Perception and Perceived Design Expertise. PROCESS macro (Hayes, 2017) was used to examine the mediation of mind perception (H2b) and the serial mediation of mind perception and perceived design expertise (H3) on the relationship between the design process (AI vs. humanized AI designer vs. human-AI collaboration vs. human) and consumer responses. Familiarity with AI services, fashion involvement, age, gender, and experience in product design were entered as covariates across the models.

The indices of mind perception were first used as a mediator. Simple mediation analyses (Model 4) with 5,000 bootstrap samples were performed. The indirect effects of design process through mind perception were significant on purchase intention (indirect effect: 0.20, 95% CI = [0.0141, 0.3904]), but not on product attitude (95% CI = [-0.0242, 0.3751]) and brand attitude (95% CI = [-0.0452, 0.2441]). Perceived experience and agency were entered as separate mediators to further examine the mediation of mind perception (see Table 24). The results showed non-significant mediation of perceived experience on the three dependent variables. Perceived agency mediated the effect of design process on product attitude (indirect effect: 0.12, 95% CI = [0.0040, 0.2554]) and purchase intention (indirect effect: 0.12, 95% CI = [0.0081, 0.2449]), but not on brand attitude (95% CI = [-0.0248, 0.1593]). Next, serial mediation analyses (Model 6) with 5,000 bootstrap samples were performed to test the serial mediation of mind perception and perceived design expertise. The indirect effects of design process through mind perception and perceived design expertise were significant on product attitude (indirect effect: 0.29, 95% CI = [0.1752, 0.4243]), purchase intention (indirect effect: 0.16, 95% CI = [0.0842, 0.2430]), and brand attitude (indirect effect: 0.21, 95% CI = [0.1306,

0.3065]). Serial mediation was significant when perceived experience and agency were separately entered as the first mediators, as shown in Table 24. Thus, the results partially supported H2b and supported H3 in the context of the four design processes (AI vs. humanized AI designer vs. human-AI collaboration vs. human).

Table 24

Separate Mediation Analyses (Study 2)

Mediation	Indirect effect	BootLLCI	BootULCI
design process → experience → product attitude	0.16	-0.0470	0.3803
design process → experience → purchase intention	0.19	-0.0134	0.4008
design process → experience → brand attitude	0.09	-0.0635	0.2412
design process → agency → product attitude	0.12*	0.0040	0.2554
design process → agency → purchase intention	0.12*	0.0081	0.2449
design process → agency → brand attitude	0.06	-0.0248	0.1593
design process → experience → design expertise → product attitude	0.26*	0.1432	0.3887
design process → experience → design expertise → purchase intention	0.14*	0.0711	0.2234
design process → experience → design expertise → brand attitude	0.18*	0.1068	0.2788
design process → agency → design expertise → product attitude	0.19*	0.1205	0.2875
design process → agency → design expertise → purchase intention	0.10*	0.0539	0.1619
design process → agency → design expertise → brand attitude	0.14*	0.0893	0.2086

Note. Asterisk (*) indicates significant indirect effects.

Model 80 with 5,000 bootstrap samples was performed to test separate parallel mediations of perceived experience and perceived agency and serial mediation simultaneously. Design process as an independent variable, perceived experience and perceived agency as the first two parallel mediators, and perceived design expertise as the second serial mediator were entered (see Figure 10). The results for all three dependent

variables (DVs) showed significant serial mediation of perceived agency and design expertise (design process → perceived agency → perceived design expertise → DVs). Other mediations as well as the serial mediation of perceived experience and design expertise (design process → perceived experience → perceived design expertise → DVs) became non-significant. The results mean that when simultaneously analyzing all parallel and serial mediators in one model, the serial mediating effect of perceived agency and design expertise overrides all other mediation effects. The results of the Model 80 analyses are presented in Table 25.

Figure 10

Parallel and Serial Mediation Analysis Model (Study 2)

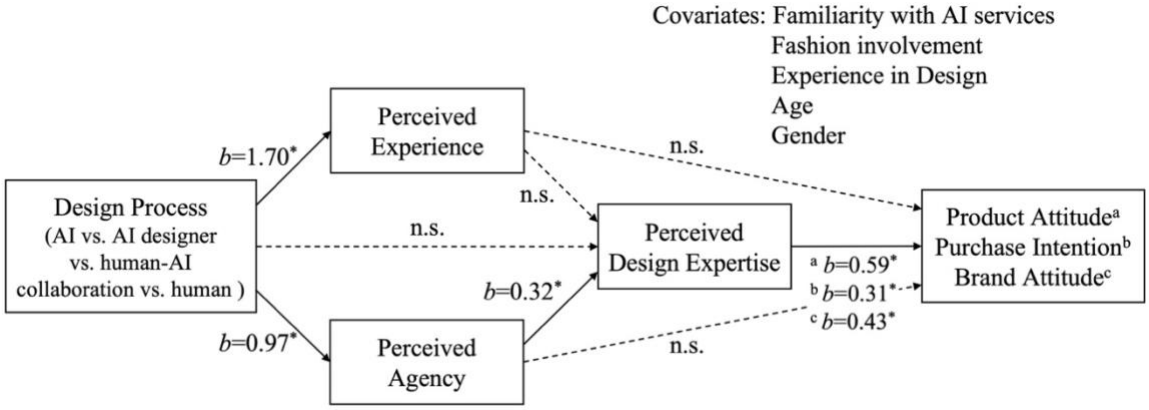


Table 25

Parallel and Serial Mediation Analysis Results (Study 2)

	Indirect effect	BootSE	BootLLCI	BootULCI
DV: Product attitude				
Total effect of design process on DV: .2001, t=2.59, p=.010; direct effect: p=.905				
Total indirect effect	0.21*	0.1038	0.0153	0.4198
design process → experience → product attitude	-0.01	0.1236	-0.2548	0.2310
design process → agency → product attitude	-0.08	0.0719	-0.2142	0.0649
design process → design expertise → product attitude	0.08	0.0641	-0.0395	0.2163
design process → experience → design expertise → product attitude	0.04	0.0676	-0.0986	0.1722
design process → agency → design expertise → product attitude	0.18*	0.0484	0.0944	0.2818
DV: Purchase intention				
Total effect of design process on DV: .1929, t=2.49, p=.014; direct effect: p=.881				
Total indirect effect	0.21*	0.1065	0.0074	0.4239
design process → experience → purchase intention	0.06	0.1400	-0.2172	0.3213
design process → agency → purchase intention	-0.01	0.0824	-0.1612	0.1572
design process → design expertise → purchase intention	0.04	0.0340	-0.0213	0.1134
design process → experience → design expertise → purchase intention	0.02	0.0370	-0.0503	0.0996
design process → agency → design expertise → purchase intention	0.10*	0.0294	0.0465	0.1613
DV: Brand attitude				
Total effect of design process on DV: .1448, t=2.54, p=.012; direct effect: p=.912				
Total indirect effect	0.14*	0.0675	0.0063	0.2719
design process → experience → brand attitude	-0.01	0.0827	-0.1728	0.1517
design process → agency → brand attitude	-0.08	0.0506	-0.1735	0.0225
design process → design expertise → brand attitude	0.06	0.0469	-0.0278	0.1576
design process → experience → design expertise → brand attitude	0.03	0.0498	-0.0713	0.1254
design process → agency → design expertise → brand attitude	0.13*	0.0352	0.0715	0.2071

Note. Asterisk (*) indicates significant indirect effects.

5.3 Discussion

Study 2 aimed to replicate the findings of Study 1 about the effect of design entity (AI vs. human) on consumer responses and mind perception (H1, H2a). The mediation of mind perception and perceived design expertise was tested in the context of four design processes (AI vs. humanized AI designer vs. human-AI collaboration vs. human; H2b, H3). Lastly, Study 2 tested the moderation of the level of incorporating human aspects into AI applications (H6).

The hypothesis testing results of Study 2 are provided in Table 26. Study 2 replicated the findings of Study 1 that consumers prefer fashion products designed by humans than AI (H1) using a short product description and a product image. Study 2 participants in the human condition formed more favorable product and brand attitudes and higher purchase intentions. Also, the Study 2 results confirmed consumers infer higher experience and agency to humans to AI (H2a). These findings were in line with the hypotheses and the findings of Study 1.

Table 26

Study 2 Hypothesis Testing Results

Hypotheses		Results	
H1	design entity (AI vs. human) → consumer responses	supported	· Participants preferred human-designed products to AI-designed products, confirmed through product attitude, purchase intention, and brand attitude.
H2a	design entity (AI vs. human) → mind perception	supported	· Participants ascribed lower experience and lower agency from AI than humans.
H2b	design process* (AI vs. humanized AI designer vs. human-AI collaboration vs. human) → mind perception → consumer responses	partially supported	· Perceived experience did not mediate the relationship between the design process and responses. · Perceived agency mediated the effect of the design process on product attitude and purchase intention but not on brand attitude.
H3	design process* (AI vs. humanized AI designer vs. human-AI collaboration vs. human) → mind perception → perceived design expertise → consumer responses	supported	· The relationships between the design process and responses were serially explained by perceived experience / agency and perceived design expertise. · When all parallel and serial mediations were entered, the serial mediation of perceived agency and perceived design expertise overrode other mediations.
H6	Moderation of human aspects incorporated into AI applications	not supported	· Participants perceived the highest experience from the entities working for human-AI collaboration, followed by a humanized AI designer and AI. · Perceived agency from AI, a humanized AI designer, and the entities working for human-AI collaboration did not significantly differ. · Perceived design expertise from AI, a humanized AI designer, and the entities working for human-AI collaboration did not significantly differ. · Negative responses to AI-designed products were mitigated when the product was described to be designed by a humanized AI designer. · The mitigating effect of human-AI collaboration was found on purchase intention and brand attitude but not product attitude.

Note. *Mediation of mind perception and perceived design expertise was tested on the effect of design *process* in Study 2.

The mediation of mind perception on the relationship between design process and consumer responses was partially supported (H2b). Mind perception mediated the relationship between design process and purchase intention when perceived experience and perceived agency were combined into one factor. Interesting results were found when perceived experience and perceived agency were separately entered; the mediation of perceived experience was non-significant, whereas perceived agency mediated the effect of design process on product attitude and purchase intention. The mediation of perceived agency was non-significant in the relationship between design process on brand attitude. In other words, participants in the four study conditions formed different levels of product attitudes and purchase intentions because of perceived agency but not of perceived experience. The findings on different mediation denote the distinction between perceived experience and perceived agency, in line with the mind perception theory (Epley & Waytz, 2010; Gray et al., 2007). Also, the findings indicate the importance of perceived agency in explaining consumer responses to fashion products affected by design process. Unexpectedly, perceived experience nor agency did not explain the relationship between design process and brand attitude. Perceived experience nor agency from the entities in design process may not be enough to explain the effect of design process on brand attitudes, which will be discussed again in the serial mediation section.

Next, Study 2 confirmed the serial mediation of mind perception and perceived design expertise in the relationship between design process and consumer responses (H3). These findings in Study 2 are especially important because the simple mediation of perceived experience was non-significant, and mediation of perceived agency varied depending on consumer responses. In contrast to the sole perceived experience or agency

that did not explain all the relationships between design process and consumer responses, the chain of perceived experience or agency and perceived design expertise explained all the relationships. Furthermore, the mind perception–perceived design expertise chain was enough to explain the relationship between design process on brand attitude. In sum, consistent with the hypothesis development and Study 1 findings, the roles of mind perception as a pre-attributional process and perceived design expertise as a subsequent mediator were confirmed in the context of four design processes.

The simultaneous parallel and serial mediation analysis yielded interesting findings. When perceived experience and agency were separately entered as parallel mediators and perceived design expertise was entered as the second serial mediator in the model, only the serial mediation of agency and design expertise (design process → agency → design expertise → responses) remained significant (see Table 25). In contrast, the sole mediation of experience, agency, or design expertise and the serial mediation of experience and design expertise (design process → experience → design expertise → responses) became non-significant. This means that when all three mediators are examined simultaneously, perceived agency–design expertise chain better explains the relationships more than the others. In other words, Study 2 participants' different responses to sweaters between the four conditions were mainly because of the agency–design expertise chain. These Study 2 findings confirm the mind perception theory literature by demonstrating that perceived agency affecting perceived design expertise is a critical factor that explains the effect of design process. In sum, consumers form the most favorable responses to fashion products designed by human designers (vs. AI-

assisted design processes) mostly because of the higher perceived design expertise affected by perceived agency.

Lastly, Study 2 tested the moderation of human aspects incorporated into AI applications (H6). It was posited that consumers' negative responses to AI-designed fashion products would be the weakest when the products are described to be designed through human-AI collaboration, followed by a humanized AI designer and AI. The hypothesized pattern was shown in perceived experience. Participants perceived the significantly highest experience from the entities working for human-AI collaboration, followed by a humanized AI designer 'Vella' and AI. Although the mean value of perceived experience was higher from the humanized AI designer than from AI, the difference was not statistically significant. This means that consumers ascribe higher experience from entities working for human-AI collaboration than AI and a humanized AI designer. The finding is in line with prior research in that human intervention in AI applications can compensate for the AI's lack of emotional ability (Huang & Rust, 2018; Peng et al., 2022). On the contrary, the current results imply that a humanized AI designer is not as effective as human-AI collaboration in increasing perceived mental ability to feel and sense emotions.

In contrast to perceived experience, unexpected findings were found in perceived agency and perceived design expertise. The results show that consumers see AI, a humanized AI designer, and human-AI collaboration to encompass similar levels of perceived agency and perceived design expertise. While the AI-assisted design process may be managed and described in different ways (i.e., designed by AI vs. by a humanized AI designer vs. through human-AI collaboration), when evaluating the ability to

intentionally act and plan, consumers may assume inevitable human work in all AI-assisted processes and thus similar perceived agency and perceived design expertise. Alternatively, given that consumers are recently becoming more aware of and sensitive to AI's enhanced cognitive and logical ability (Chui et al., 2022), design by AI or a humanized AI designer are likely deemed to have similar cognitive ability to human-AI collaboration. These findings can also be interpreted from what was explained in the mind perception theory; the theory explains that people perceive low to moderate levels of agency while low experience from computers (see Figure 4). The advantageous effects of a humanized AI designer or human-AI collaboration may not be stronger for enhancing the moderate perceived agency from AI compared to enhancing the low perceived experience from AI.

Study 2 shows interesting findings when it comes to the moderation of human aspects incorporated into AI applications on product attitude, purchase intention, and brand attitude. Despite the different directions from the hypothesized pattern, the results imply that incorporating human aspects into the descriptions of AI-assisted design process generally alleviates consumers' negative responses to AI-designed fashion products. For all three of product attitude, purchase intention, and brand attitude, negative responses were lessened when the sweater was described to be designed by a humanized AI designer, thus not significantly lower than those in the human condition. The mitigating effects of human-AI collaboration were found on purchase intention and brand attitude, which were not significantly lower than those in the human condition. Taken together, the advantageous effects of human aspects incorporated into AI applications on consumer responses are supported. These findings align with the existing studies that

confirmed the positive effect of human aspects in AI applications on consumer perception (e.g., Huang & Rust, 2018, 2022; Peng et al., 2022).

It is also important to note that, while the description of a sweater designed by a humanized AI designer or through human-AI collaboration enhanced consumer responses, they also show non-significant differences from the responses to a sweater designed by AI. This means that the description 'Designed by AI' is not necessarily tremendously inferior to the description 'Designed by an AI designer' or 'Designed through human-AI collaboration,' which calls for further examination of each response (i.e., product attitude, purchase intention, brand attitude). Study 2 participants formed similar product attitudes toward the sweater designed by AI and through human-AI collaboration, which was significantly lower than the attitudes toward the human-designed sweater. A humanized AI designer was especially effective in increasing positive product attitudes. Such patterns differ from purchase intention and brand attitude as both a humanized AI designer and human-AI collaboration enhance purchase intention and brand attitude. Considering (a) the serial mediation of perceived agency and design expertise and (b) the similar levels of perceived agency and design expertise across the AI-assisted design processes, consumers are likely to form similar product attitudes that are immediately formed after seeing the product. On the other hand, such a pattern may not be as much obvious in the case of purchase intention and brand attitude that are more complex constructs with multi-faceted determinants (Dick & Uhrich, 2017; Fishbein & Ajzen, 1975; Mitchell, 1986). The findings offer a differentiated understanding by the different types of consumer responses that would be useful for practitioners, which are described in the practical implications section.

Chapter 6. Discussion and Implications

Chapter 6 discusses the study findings and positions the study in the literature. Next, theoretical and practical implications drawn from the study findings are presented. The study's limitations and suggestions for future research are provided at the end.

6.1 General Discussion of Findings

Generative AI is one of the fastest moving and most influential technological trends in the retail landscape. With its capability to focus on creative problem-solving and generate creative outputs ranging from texts to images and videos, AI in the fashion product design process is experiencing a dynamic shift and is expected to bring more productive businesses (Harreis et al., 2023). This research aimed to understand how consumers respond to AI applications in the fashion design process by answering the three research questions: How do consumers evaluate AI-designed (vs. human-designed) fashion products? (RQ1); How do consumers perceive the capability of AI in the fashion product design process? (RQ2); What boundary conditions may alter the effects of design entity on consumer responses to the designed fashion products? (RQ3). Two online experiments built upon the mind perception theory tested the research hypotheses.

6.1.1 Effect of Design Entity on Consumer Responses

To answer RQ1, the effects of design entity (AI vs. human) on consumer responses were tested by comparing consumers' product attitudes, purchase intentions, and brand attitudes toward the human-designed versus AI-designed fashion products. The two experiments in this research demonstrated consumer preference for human-designed products over AI-designed products. The findings are consonant with the literature that

confirmed people's resistance to the judgments or work made by AI compared to by humans (e.g., Agudo et al., 2022; Dietvorst et al., 2015; Granulo et al., 2021; Im & Lee, 2023). In line with and extending what Xu and Mehta (2022) uncovered, consumers like human-designed fashion products more than AI-designed ones. Such preference is also found in purchase intention and brand attitude. Importantly, it was confirmed that human designers are perceived to have higher mental capacity to feel and sense emotions (experience) and cognitive ability to act or plan (agency), across the two experiments. These findings are consistent with what mind perception theory explains.

Additionally, important findings are drawn by comparing the results of Study 1 and Study 2 on the effects of design entity on consumer responses. Although the significant preferences for human-designed over AI-designed fashion products are confirmed in both studies, the effects seem to be potentially diminished to some degree when product images are shown to consumers. The differences between the human and AI conditions in product attitude, purchase intention, and brand attitude were significant at .001 levels ($p<.001$ for all three) in Study 1 which did not provide product images. On the other hand, the differences became slightly lessened (product attitude: $p<.001$, purchase intention: $p=.057$, brand attitude: $p=.038$) in Study 2 with a product image. It is possible that the product stimuli used in Study 2 affected the participants' responses. Alternatively, these findings may be interpreted as consumers' negative bias toward AI-designed fashion products may be alleviated or strengthened depending on the final designed products. This possible explanation can comprehensively explain the mixed findings on people's responses to AI-generated creative work (e.g., Hong, 2018, Hong & Curran, 2019; Lopez et al., 2019; Ragot et al., 2020). For example, Hong and Curran

(2019) found that people put a higher artistic value on human-designed artwork than on AI-designed one, but such differences do not always predict more negative evaluations of AI-designed artwork. Likewise, although human-designed fashion products are generally preferred over AI-designed products, the degree of strength in such preference may vary depending on the final product design. It will be beneficial if future research explores whether evaluations of AI-designed versus human-designed products will differ depending on particular design elements or design themes. In sum, this research answers RQ1 by showing that consumers evaluate human-designed fashion products more positively than AI-designed products.

6.1.2 Mediation of Mind Perception and Perceived Design Expertise

The roles of mind perception and perceived design expertise from AI and humans in explaining the effect of design entity were tested to answer RQ2. In addition to the findings that consumers ascribe higher minds to humans than AI, the two experiments demonstrated consumers perceive higher design expertise from human designers than AI. More importantly, mind perception and the mind perception–perceived design expertise chain mediate the relationships between design entity and consumer responses. Consumers respond to human-designed fashion products more positively than AI-designed ones, because consumers believe human designers are more capable of feeling and sensing emotions and cognitively and intentionally acting or planning. Furthermore, such mind perception consequently affects perceived design expertise, which is ultimately the reason why consumers prefer human-designed fashion products. Compared to perceived experience, perceived agency mainly explains consumer responses toward the products designed by humans or through AI-assisted processes. In other words,

products designed by humans are preferred mostly because human designers are perceived to be more competent than AI due to their cognitive and intentional acting or planning rather than their emotional capacity.

While Study 1 tested the effect of design entity (AI vs. human), Study 2 tested the effect of the four design processes that include varying levels of human aspects in AI applications (AI vs. humanized AI designer vs. human-AI collaboration vs. human). The simple mediation analyses of mind perception in Study 1 and Study 2 show the differences between the effect of design entity and the effect of design process. Both perceived experience and agency explain the effects of design entity (AI vs. human) on the three consumer responses. On the other hand, perceived experience does not solely explain the relationships between design process and the three consumer responses. This means that the explaining role of perceived experience is not enough when the varying human aspects of AI applications (i.e., AI vs. humanized AI designer vs. human-AI collaboration) are considered. Perceived agency explains the effect of design process on product attitude or purchase intention, but not brand attitude. This means that the explaining role of perceived agency is not enough for brand attitude when considering the varying human aspects of AI applications.

These findings are important as they have two contributions. First, the distinction between perceived experience and perceived agency is validated, which is described in detail in the theoretical implications section below (see 6.2.1). Accordingly, the difference in the explaining power between perceived experience and agency is proven by comparing the effect of design entity and design process. Second, the differences between product attitude, purchase intention, and brand attitude are proven. Both

perceived experience and perceived agency do not explain the effect of design entity or process on brand attitude, unlike product attitude or purchase intention. This confirms that brand attitude is differentiated from product attitude or purchase intention because it is a complex construct that may encompass diverse factors (Dick & Uhrich, 2017; Mitchell, 1986).

Mind perception and perceived design expertise serially explain both the effects of design entity and design process on consumer responses. Across the effects of design entity and design process, the differences in consumer responses are due to perceived design expertise which is affected by mind perception. The parallel and serial mediation analysis in one model shows the strong effects of perceived agency and perceived design expertise in explaining the effect of design entity or design process. When the mediating effects of perceived experience, agency, and design expertise were simultaneously analyzed, perceived design expertise and the perceived agency–design expertise chain overrode other mediations for the effect of design entity. Similarly, the perceived agency–design expertise chain overrode other mediations for the effect of design process on consumer responses.

The findings yield two important contributions. First, the importance of perceived design expertise is verified in explaining how consumers evaluate fashion products. Perceived design expertise remains strong enough to explain consumers' preference for human-designed products over AI-designed ones. More importantly, both two experiments confirm the critical role of perceived design expertise as the underlying mechanism between mind perception and consumer evaluation. As the literature on design studies has long emphasized, perceived design expertise is a robust heuristic cue

that affects the persuasion of the design and design success achievement (Ratneshwar & Chaiken, 1991; Schreier et al., 2012). This study extends the understanding of perceived design expertise by confirming its crucial impact in the context of the AI-assisted design process. Second, the pivotal role of perceived agency is again confirmed between design entity or design process and consumer responses. Unlike perceived experience, the mediation of perceived agency–design expertise chain remains strong enough. Compared to perceived emotional capabilities, perceived agentic capabilities of the designers are the key to explaining perceived design expertise and different responses to the products designed by humans or through AI-assisted processes. Furthermore, human-designed products are more positively evaluated mostly because humans are perceived to be more competent than AI due to their cognitive and intentional acting or planning. This may imply the potential that consumers can like AI-designed products when AI makes further, elaborate progress enhancing perceived agency. Future research will be beneficial to explore such possibilities. In essence, this research answers RQ2 by demonstrating that consumers perceive lower design expertise from AI than humans in the fashion design process, mainly due to the relatively low intentional and cognitive abilities inferred from AI.

6.1.3 Moderation of Product Type, Perceived Threat, and Human Aspects

To answer RQ3, this study tested the moderation of product type, perceived threats from AI, and the level of human aspects incorporated into AI applications. First, the moderating effect of product type (self-expressive vs. functional) was examined in Study 1 to see if product type alters consumers' negative responses to AI-designed products. The results show that the effect of design entity does not significantly differ

between self-expressive and functional products. Furthermore, the mind perception–perceived design expertise chain explains the superior effect of humans over AI for both self-expressive and functional products.

These findings exhibit different results from the expectations and the literature that suggested the moderation of product type (Ruan & Mezei, 2022; Xu & Mehta, 2022, Zhang et al., 2022). The current study's findings should be carefully interpreted, since evidence for the non-significant moderation of product type may not be conclusive. This study used fashionable jacket versus insulated jacket to operationalize self-expressive versus functional products. Considering this, the findings imply that preference for human-designed (vs. AI-designed) fashion products resulting from mind perception and perceived design expertise holds true regardless of product type when it comes to the same product category. Future studies can test the moderation of product type using various product categories representing self-expressive versus functional conditions. For example, future studies can have two different extreme product usage motivations or characteristics (Sen & Lerman, 2007). Additionally, considering that consumers' preference for machine-generated creative works in prior research was found in simple line sketches (Lopez et al., 2019), it will be interesting to explore the effect of design types that might be differently affected by mind perception and perceived design expertise. In sum, RQ3 is firstly answered by revealing that consumers' preference for human-designed over AI-designed fashion products does not differ between self-expressive and functional products within the same product category.

Second, the moderating effect of perceived threats from AI was tested in Study 1. The results indicate that the effect of design entity does not significantly differ between

consumers with higher and lower perceived threats from AI. Regardless of perceived threats from AI, consumers respond more positively to human-designed products than AI-designed ones. While the effects of design entity on consumer responses are not affected, the serial mediation of mind perception and perceived design expertise on product attitude is moderated by perceived threats from AI. According to the results of Study 1, mind perception and perceived design expertise more (vs. less) strongly explain why consumers prefer human-designed products in case consumers find AI more (vs. less) intimidating. On the other hand, moderation is not significant in the serial mediation for brand attitude and purchase intention.

The findings again prove the subtle but clear nuances between product attitude, purchase intention, and brand attitude. The differences in moderated mediation of mind perception and perceived design expertise between the three consumer responses may be attributable to that product attitude is more immediately formed than purchase intention and brand attitude. Contrastingly, the mediation for purchase intention may not highly differ depending on perceived threats from AI, because those with higher perceived AI threats may not consider purchasing AI-designed products regardless of perceived mind and design expertise. Furthermore, the findings may imply potential implicit effect of perceived threats on consumer responses that are product-related. If consumers develop irrational feelings of threats from AI, their inferences about AI's mind and expertise affect their responses to AI-related products more, which can unconsciously impact their behavioral intentions. Future studies might employ implicit measures to test further whether consumers' fear of AI technology affects their evaluation of AI-related products, such as implicit association tests or affective priming tasks (Fazio et al., 1995; Greenwald

et al., 1998). In short, this study secondly answers RQ3 by showing that preference for human-designed over AI-designed fashion products holds regardless of perceived threats from AI, while the mediation of mind perception and perceived design expertise for product attitude is stronger for those with higher perceived threats from AI.

Thirdly and lastly, Study 2 tested the moderation of incorporating human aspects into AI applications. The results confirm that incorporating human aspects when introducing AI-designed fashion products alleviates consumers' negative responses. Although not entirely the same as the hypothesized specific patterns, the findings align with the literature on the positive effects of humanizing AI on consumer perceptions (e.g., David-Ignatieff et al., 2023; Huang & Rust, 2018, 2022; Peng et al., 2022). When it comes to perceptions of the entities in the design process, human-AI collaboration is the most beneficial in increasing perceived experience compared to AI or a humanized AI designer. Consumers' negative responses are generally mitigated to some degree when fashion products are described to be designed by a humanized AI designer or through human-AI collaboration, making the differences from the response toward human-designed products non-significant. Humanized AI designer is especially effective in increasing all three types of consumer responses, while the advantageous effect of human-AI collaboration mainly applies to purchase intention and brand attitude but not product attitude.

The differences between a humanized AI designer and human-AI collaboration may have two possible explanations. On the one hand, it is speculated that the advantage of human-AI collaboration in increasing perceived experience is not largely transmitted to consumer responses. This may be because, as the parallel and serial mediation analysis

indicates, perceived agency and design expertise are the keys to consumer responses to products designed by humans or through AI-assisted processes. On the other hand, it may be due to consumers' higher expectations of products designed through human-AI collaboration compared to those designed by AI or a humanized AI designer. Consumer behavior literature has described that consumers form an initial expectation of a specific product and then form a satisfaction or post-evaluation based on their confirmation and expectation on which that confirmation was based (Marks & Kamins, 1988; Oliver, 1980). Given that human-AI collaboration represents the highest level of human involvement in AI applications, consumers may expect higher quality from products designed through human-AI collaboration, which may lead to relatively low product attitudes after seeing the product. It will be interesting to explore consumer perceptions and expectations of a humanized AI designer versus human-AI collaboration further. To sum up, RQ3 is lastly answered by confirming that incorporating human aspects when introducing AI-designed fashion products can help alleviate consumers' negative responses.

6.2 Implications

6.2.1 Theoretical Implications

This study contributes to the literature on the applications of generative AI in retail, focusing on the fashion design process. First, the study findings help understand consumer perception and evaluation of AI-designed products. Extending the empirical knowledge on consumer responses to AI-generated creative work to the fashion design process (e.g., Agudo et al., 2022; Chamberlain et al., 2018; Hong et al., 2022; Ragot et

al., 2020), this study confirms the superior effects of humans as a design entity compared to AI. Moreover, such effects are explained by mind perception and perceived design expertise, offering an in-depth understanding of why consumer responses to AI- versus human-designed products are consequently affected. While the findings support the view that consumers generally evaluate human-designed products more favorably than AI-designed ones, it is important to continue to examine preferences for humans over AI. This is because consumer preferences may have the potential to be changed contingent on situation-specific factors, consumer characteristics, or consumption contexts. Generative AI is experiencing unprecedented technological advances that trigger transformations in academia and business (Harreis et al., 2023; Spirling, 2023). Therefore, consumers may experience turbulence in their perceptions of AI, which consequently result in varying responses to AI-generated work. For example, Zhang et al. (2022) found that consumers are willing to pay more for AI-designed products than human-designed ones due to curiosity regarding AI design, and such an effect is attenuated when consumers have high knowledge of AI design. Given that generative AI is becoming more prevalent in the consumer environment, this study offers empirical findings that help understand the evaluation of consumer products designed by generative AI.

Second, this study helps advance the theoretical knowledge of the mind perception of AI versus humans. The current study demonstrates that consumer preference for human-designed fashion products is a consequence of mind perception. Comparing mind perception of AI versus humans helps advance the knowledge of not only product design but also other AI-related tasks, such as customer services and product recommendations, confirming the existing literature (e.g., Gray & Wegner, 2012;

Söderlund & Oikarinen, 2021; Wu et al., 2021). Moreover, this study reveals that perceived agency plays a significant role in contrast to perceived experience, thus validating the distinction between the two. As indicated in the mind perception theory literature, the correlation between perceived experience and agency was high in the current study. Still, the findings on the mediation of perceived experience and perceived agency suggest that they are distinctive sub-dimensions of mind perception. In addition, the important role of perceived design expertise is confirmed. The effects of design entity and design process on consumer responses are explained by perceived design expertise which is affected by mind perception. These findings are in agreement with the existing literature suggesting that mind perception serves as a pre-attributional process that derives the third, situation-specific factor (Epley & Waytz, 2010; Premack & Woodruff, 1978). Previous studies tested the third factor to explain consumer evaluation of virtual agents (e.g., humanness and usefulness from Söderlund's (2022) study, morality from Söderlund and Oikarinen's (2021) study, and anthropomorphism from Yam et al.'s (2022) study). Extending the literature on mind perception to AI applications in the fashion design process, this study corroborates the critical role of perceived design expertise.

Lastly, examining the boundary conditions of the effect of design entity broadens the understanding of AI applications in the fashion design process. The advantageous effects of humans over AI as design entity are confirmed across different product types in the same product categories and perceived threats from AI. Given the study context and moderated mediation of perceived threats from AI, this study proposes room to further examine the moderation by varying study contexts, such as different types of consumer

responses or distinct product categories. Furthermore, varying levels of human aspects in AI applications (AI vs. humanized AI designer vs. human-AI collaboration) lead to different ratings between mind perception, perceived design expertise, and consumer responses. As the literature on experience gap and human-AI collaboration suggested (Fenwick & Molnar, 2022; Gray & Wegner, 2012; Srinivasan & Sarial-Abi, 2021), human intervention in the AI-assisted design process assures a significant increase in perceived experience. On the other hand, human aspects are not as powerful in enhancing perceived agency and perceived design expertise as in enhancing perceived experience. The findings echo what feeling economy literature suggests; humans' strength of empathetic ability is to be prominent as AI evolves its rationality and objectivity (Ferràs-Hernández, 2018; Pedersen, 2021; Rust & Huang, 2021). These implications are especially helpful for the areas where empathetic and emotional values are highly appreciated, such as customer services, customer relationship management, or hospitality management.

6.2.2 Practical Implications

The study findings offer practitioners useful implications regarding the applications of generative AI in the design process. First, practitioners can have insights into how to overcome consumers' negative bias toward AI-designed fashion products. This is critical because the current study's findings imply that bias affects important marketing outcomes such as consumer attitude and purchase intention. Negative bias toward AI-designed products is mainly specified by the low perceived agency and perceived design expertise from AI. These patterns are captured similarly across the different product types (symbolic vs. functional) in the same category and consumers

with varying levels of perceived threats from AI. It can be concluded that product design in the fashion realm, at least when comparing humans versus AI, is where consumers value the agentic and intentional abilities of the design entity relatively more than emotional abilities. This is consequently why consumers would prefer human-designed products over AI-designed products. In this vein, practitioners who plan to employ AI-assisted design processes are recommended to actively utilize and promote AI's advantages in contributing to agency. For example, as industry professionals suggest (e.g., Harreis et al., 2023; MIT Technology Review Insights, 2021), brands can advertise that AI benefits the design process by accelerating efficient and precise decision-making as well as by automating labor-intensive processes, which can ultimately enhance overall agentic value and design expertise.

Second, practitioners are recommended to deploy and emphasize humans' emotional and experiential abilities when implementing AI applications in business. Along with the literature that stresses the importance of humans' empathy (Ferràs-Hernández, 2018; Pedersen, 2021; Rust & Huang, 2021), this study points out that the most outstanding strength in humans compared to AI is perceived experience. Extending these to fashion design, this study empirically shows that perceived experience is significantly intensified when the product is described to be designed through human-AI collaboration. This is important because more and more consumers are becoming aware of AI's enhanced cognitive and intentional capacity quickly. AI may be deemed to overweigh humans' capabilities, be an equal member of the team, or lead to job replacement or mass unemployment depending on domains or tasks (Chalmers, 2016; Pan & Froese, 2023; Yam et al., 2023). Accordingly, it will be worthwhile to emphasize

that humans and AI collaborate and complement one another by highlighting humans' contributions to understanding emotional needs and utilizing feeling intelligence. These implications benefit not only the fashion industry but also other retail sectors where perceived experience of involved entities can be crucial, such as customer services, customer relationship management, or hospitality management.

Thirdly, the study findings recommend that practitioners who adopt AI in the design process establish tailored strategies based on their desired marketing outcomes. Both a humanized AI designer and human-AI collaboration increase purchase intention and brand attitude whereas the two exhibit different patterns pertaining to product attitude. A humanized AI designer is especially effective for enhancing product attitude, but human-AI collaboration is not as much successful, leading the product attitude to be significantly lower than the attitude toward human-designed products. These findings provide actionable guidelines for brands. If a brand's business goal is to generate positive consumer attitudes toward a particular product or product line in the short term, introducing the product as designed by a humanized AI designer can be one of the most promising tactics. Contrarily, human-AI collaboration can also be equally beneficial if the marketing goal is to raise purchase intentions or promote favorable brand attitudes, although it may not produce largely successful outcomes on product attitude at first. Furthermore, the context-dependent role of mind perception and perceived design expertise is proven for product attitude by the moderation of perceived threats from AI. Practitioners who aim for product attitude can understand target consumers' general perceived threats from AI and adjust marketing messages about AI's mind and design expertise accordingly when promoting their products. For example, if a brand's target

consumers are characterized by high technology avoidance due to fear, the brand can attempt to minimize potential negative product attitudes by educating customers about prospected advantages of AI in enhancing the overall mind capacity and expertise of entities in the design process. In essence, incorporating human aspects increases the likelihood that consumers will more positively respond to products from AI-assisted design processes. However, specific marketing goals and consumer characteristics such as perceived threats from AI should be carefully considered.

Finally, as briefly mentioned above (see 5.3 and 6.1.1 for details of study findings), it should be noted that the description 'Designed by AI' is not necessarily highly inferior to the description 'Designed by an AI designer' or 'Designed through human-AI collaboration.' It is true that a humanized AI designer or human-AI collaboration relieves consumers' negative responses so the difference from the responses toward human-designed products becomes non-significant. Still, they are also not significantly higher than the responses toward AI-designed products. Thus, the findings do not indicate that the description 'Designed by AI' should always be avoided; rather, the findings may imply the potential of changing negative bias toward AI-designed products.

6.3 Limitations and Future Research

This study has limitations that can be addressed in future research. First, although the two online experiments adopted multiple covariates based on the existing literature on AI and consumer behavior, the generalizability of the results to specific consumer groups may be limited. This study used the covariates to rule out potential confounding effects

and provide an understanding of overall consumer responses to AI- versus human-designed fashion products. Future studies exploring specific consumer groups' responses will be helpful to make the results applicable from a marketing perspective for unique cases. When a brand's target persona is primarily defined by a narrow age range, for example, future studies can recruit participants in that age group to focus on their responses.

Second, future studies can employ various study settings to reduce the potential impact of the operational characteristics of the current study. For example, this study used fashionable versus insulated jackets to operationalize symbolic versus functional product types. While the critical role of perceived agency over experience was confirmed in this study, it is possible that the role of experience becomes more salient with other categories of fashion products for which the design entity's emotional intelligence is highly valued. It will be beneficial for future studies to use various stimuli with different product usage motivations or characteristics (Sen & Lerman, 2007), such as handbags or pumps versus medical gowns or bunker gear. Likewise, perceived threats from AI were measured to test the moderation in this study. Future studies can manipulate the levels of perceived threats from AI by developing fictitious scenarios or stimuli and temporarily priming perceived threats from AI to test the moderation further.

Third, it should be considered that the participants living in the U.S. and fluent in English were recruited online. The evidence for the adequateness of using online recruitment platforms has been consistently documented (Difallah et al., 2018; Eyal et al., 2022; Kees et al., 2017). However, this does not necessarily mean that the empirical findings reported herein can be generalized to consumers in other cultural environments.

For example, those who are not fluent in English or do not have easy access to online recruitment platforms may shape unique characteristics, which may not be captured in this study. Therefore, future studies can be extended to understand consumer responses to AI applications in the design process in diverse study contexts.

Lastly, future studies can employ various methods of measuring consumer evaluations of AI-designed products. This study used participants' own self-reported measures of attitudes and purchase intention. Other measures that are more related to price or monetary perceptions, such as perceived cost structure (Nunes et al., 2004), perceived price fairness (Xia et al., 2004), or willingness to pay premium price cost (Casidy & Wymer, 2016), will be beneficial to provide insights into the pricing structures of AI-designed products. Additionally, implicit attitudes can be assessed using the frequently used procedures in prejudice studies, for example, affective priming method (Fazio et al., 1986) or Implicit Association Test (IAT; Nosek et al., 2007).

References

Aaker, J. L. (1997). Dimensions of brand personality. *Journal of Marketing Research*, *34*(3), 347-356.

Aaker, J. L. (1999). The malleable self: The role of self-expression in persuasion. *Journal of Marketing Research*, *36*(1), 45-57.

Achabou, M. A., Dekhili, S., & Codini, A. P. (2020). Consumer preferences towards animal-friendly fashion products: an application to the Italian market. *Journal of Consumer Marketing*, *37*(6), 661-673.

Adair, J. G. (1984). The Hawthorne effect: a reconsideration of the methodological artifact. *Journal of Applied Psychology*, *69*(2), 334.

Agudo, U., Arrese, M., Liberal, K. G., & Matute, H. (2022). Assessing emotion and sensitivity of AI artwork. *Frontiers in Psychology*, *13*. 879088.

Ahn, J., Kim, J., & Sung, Y. (2021). AI-powered recommendations: the roles of perceived similarity and psychological distance on persuasion. *International Journal of Advertising*, *40*(8), 1366-1384.

Ajzen, I., & Fishbein, M. (1977). Attitude-behavior relations: A theoretical analysis and review of empirical research. *Psychological Bulletin*, *84*(5), 888-918.

Alicke, K., Dilda, V., Görner, S., Mori, L., Rebuffel, P., Reiter, S., and Samek, R. (2021, April 30). Succeeding in the AI supply-chain revolution. *McKinsey & Company*. https://www.mckinsey.com/industries/metals-and-mining/our-insights/succeeding-in-the-ai-supply-chain-revolution

Anantrasirichai, N., & Bull, D. (2022). Artificial intelligence in the creative industries: a review. *Artificial Intelligence Review*, *55*(1), 589-656.

Appel, M., Izydorczyk, D., Weber, S., Mara, M., & Lischetzke, T. (2020). The uncanny of mind in a machine: Humanoid robots as tools, agents, and experiencers. *Computers in Human Behavior*, *102*, 274-286.

Ardelet, C., Slavich, B., & de Kerviler, G. (2015). Self-referencing narratives to predict consumers' preferences in the luxury industry: A longitudinal study. *Journal of Business Research*, *68*(9), 2037-2044.

Babin, B. J., Darden, W. R., & Griffin, M. (1994). Work and/or fun: measuring hedonic and utilitarian shopping value. *Journal of Consumer Research*, *20*(4), 644-656.

Baek, T. H., Kim, J., & Yu, J. H. (2010). The differential roles of brand credibility and brand prestige in consumer brand choice. *Psychology & Marketing*, *27*(7), 662-678.

Bakpayev, M., Baek, T. H., van Esch, P., & Yoon, S. (2022). Programmatic creative: AI can think but it cannot feel. *Australasian Marketing Journal*, *30*(1), 90-95.

Baltas, G., Kokkinaki, F., & Loukopoulou, A. (2017). Does variety seeking vary between hedonic and utilitarian products? The role of attribute type. *Journal of Consumer Behaviour*, *16*(6), e1-e12.

Banerjee, S. (2021, May 25). Humanizing AI: A case for cognitive design thinking and custom AI. *Forbes.* https://www.forbes.com/sites/forbestechcouncil/2021/05/25/humanizing-ai-a-case-for-cognitive-design-thinking-and-custom-ai/?sh=d15d9fd4a246

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers. *Industrial Management & Data Systems*,*119*(7), 1411-1430.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, *107*(2), 238-246.

Berisha, B., & Lobov, A. (2021, July). Overview and Trends for Application of AI Methods for Product Design. In *2021 IEEE 19th International Conference on Industrial Informatics (INDIN)* (pp. 1-8). IEEE.

Berlyne, D. E. (1970). Novelty, complexity, and hedonic value. *Perception & Psychophysics*, *8(*5), 279-286.

Black, T. R. (1999). *Doing quantitative research in the social sciences: An integrated approach to research design, measurement and statistics*. SAGE publications.

Blanas, S., Gancia, G., & Lee, S. Y. (2019). Who is afraid of machines?. *Economic Policy*, *34*(100), 627-690.

Bleier, A., & Eisenbeiss, M. (2015). The importance of trust for personalized online advertising. *Journal of Retailing*, *91*(3), 390-409.

Bloch, P. H. (1995). Seeking the ideal form: Product design and consumer response. *Journal of Marketing*, *59*(3), 16-29.

Bray, J. H., & Maxwell, S. E. (1985). *Multivariate analysis of variance. Sage university paper series on quantitative applications in the social sciences*. Newbury Park, CA: Sage.

Bye, E. K. (2010). *Fashion design.* Oxford, UK. Berg Publishers.

Cadario, R., Longoni, C., & Morewedge, C. K. (2021). Understanding, explaining, and utilizing medical artificial intelligence. *Nature Human Behaviour*, *5*(12), 1636-1642.

Campbell, C., Plangger, K., Sands, S., & Kietzmann, J. (2022). Preparing for an era of deepfakes and AI-generated ads: A framework for understanding responses to manipulated advertising. *Journal of Advertising*, *51*(1), 22-38.

Cao, L. (2021). Artificial intelligence in retail: applications and value creation logics. *International Journal of Retail & Distribution Management*, *49*(7), 958-976.

Casidy, R., & Wymer, W. (2016). A risk worth taking: Perceived risk as moderator of satisfaction, loyalty, and willingness-to-pay premium price. *Journal of Retailing and Consumer Services*, *32*, 189-197.

Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. *Journal of Marketing Research*, *56*(5), 809-825.

Chae, B., & Hoegg, J. (2013). The future looks "right": Effects of the horizontal location of advertising images on product attitude. *Journal of Consumer Research*, *40*(2), 223-238.

Chalmers, D. (2016). The singularity: A philosophical analysis. *Journal of Consciousness Studies*, *17*(9–10), 7–65.

Chamberlain, R., Mullin, C., Scheerlinck, B., & Wagemans, J. (2018). Putting the art in artificial: Aesthetic responses to computer-generated art. *Psychology of Aesthetics, Creativity, and the Arts*, *12*(2), 177-192.

Chan, C., Berger, J., & Van Boven, L. (2012). Identifiable but not identical: Combining social identity and uniqueness motives in choice. *Journal of Consumer Research*, *39*(3), 561-573.

Chang, Y. P., & Li, J. (2022). Seamless experience in the context of omnichannel shopping: scale development and empirical validation. *Journal of Retailing and Consumer Services*, *64*, 102800.

Chayka, K. (2023, April 7). A.I. pop culture is already here. *The New Yorker*. https://www.newyorker.com/culture/infinite-scroll/ai-pop-culture-is-already-here

Chen, Y., Li, X., & Zhang, S. (2020). Structured latent factor analysis for large-scale data: Identifiability, estimability, and their implications. *Journal of the American Statistical Association*, *115*(532), 1756-1770.

Chernev, A., Hamilton, R., & Gal, D. (2011). Competing for consumer identity: Limits to self-expression and the perils of lifestyle branding. *Journal of Marketing*, *75*(3), 66-82.

Child, D. (2006). *The essentials of factor analysis*. A&C Black.

Chinchanachokchai, S., Thontirawong, P., & Chinchanachokchai, P. (2021). A tale of two recommender systems: The moderating role of consumer expertise on artificial intelligence based product recommendations. *Journal of Retailing and Consumer Services*, *61*, 102528.

Choi, S., Mattila, A. S., & Bolton, L. E. (2021). To err is human (-oid): how do consumers react to robot service failure and recovery?. *Journal of Service Research*, *24*(3), 354-371.

Christensen, J. (2023, February 22). Most Americans are uncomfortable with artificial intelligence in health care, survey finds. *CNN*. https://www.cnn.com/2023/02/22/health/artificial-intelligence-health-care/index.html

Chui, M., Hall, B., Mayhew, H., Singla, A., & Sukharevsky, A. (2022, December 6). The state of AI in 2022—and a half decade in review. *McKinsey & Company.* https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2022-and-a-half-decade-in-review#/

Ciuchita, R., Gummerus, J. K., Holmlund, M., & Linhart, E. L. (2022). Programmatic advertising in online retailing: consumer perceptions and future avenues. *Journal of Service Management*, *34*(2), 231-255.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155-159.

Colgate, E., Wannasuphoprasit, W., & Peshkin, M. (1996). Cobots: Robots for collaboration with human operators. In *Proceedings of the ASME Dynamic Systems and Control Division*, New York, 58, 433-439.

Cortina, J. M. (1993). What is coefficient alpha? An examination of theory and applications. *Journal of Applied Psychology*, *78*(1), 98.

Creswell, J. W. (2014). *A concise introduction to mixed methods research*. SAGE publications.

Crilly, N., Moultrie, J., & Clarkson, P. J. (2004). Seeing things: consumer response to the visual domain in product design. *Design studies*, *25*(6), 547-577.

Cross, N. (2004). Expertise in design: an overview. *Design studies*, *25*(5), 427-441.

Cross, N., Christiaans, H., & Dorst, K. (1994). Design expertise amongst student designers. *Journal of Art & Design Education*, *13*(1), 39-56.

Cui, Y. G., van Esch, P., & Jain, S. P. (2022). Just walk out: the effect of AI-enabled checkouts. *European Journal of Marketing*, *56*(6), 1650-1683.

Curran, P. G. (2016). Methods for the detection of carelessly invalid responses in survey data. *Journal of Experimental Social Psychology*, *66*, 4-19.

Das, M., Jebarajakirthy, C., & Sivapalan, A. (2022). How consumption values and perceived brand authenticity inspire fashion masstige purchase? An investigation. *Journal of Retailing and Consumer Services*, *68*, 103023.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*(1), 24-42.

David-Ignatieff, A., Buzeta, C., De Pelsmacker, P., & Ben Dahmane Mouelhi, N. (2023). This embodied conversational agent looks very human and as old as I feel! The effect of perceived agent anthropomorphism and consumer-agent age difference on brand attitude. *Journal of Marketing Communications*, 1-29.

Dean, A., & Voss, D. (Eds.). (1999). *Design and analysis of experiments*. New York, NY: Springer New York.

DeLong, M. R., Minshall, B., & Larntz, K. (1986). Use of schema for evaluating consumer response to an apparel product. *Clothing and Textiles Research Journal*, *5*(1), 17-26.

Deng, S., Tan, C. W., Wang, W., & Pan, Y. (2019). Smart generation system of personalized advertising copy and its application to advertising practice and research. *Journal of Advertising*, *48*(4), 356-365.

Dhar, R., & Wertenbroch, K. (2000). Consumer choice between hedonic and utilitarian goods. *Journal of Marketing Research*, *37*(1), 60-71.

Dick, C., & Uhrich, S. (2017). Ending a sponsorship relationship: consumers' responses toward a forced versus a chosen exit. *European Sport Management Quarterly*, *17*(2), 152-170.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, *144*(1), 114-126.

Difallah, D., Filatova, E., & Ipeirotis, P. (2018, February). Demographics and dynamics of mechanical turk workers. In *Proceedings of the eleventh ACM international conference on web search and data mining* (pp. 135-143).

Ding, J., Tarokh, V., & Yang, Y. (2018). Model selection techniques: An overview. *IEEE Signal Processing Magazine*, *35*(6), 16-34.

Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of price, brand, and store information on buyers' product evaluations. *Journal of Marketing Research*, *28*(3), 307- 319.

Du, S., & Xie, C. (2021). Paradoxes of artificial intelligence in consumer markets: Ethical challenges and opportunities. *Journal of Business Research*, *129*, 961-974.

Epley, N., & Waytz, A. (2010). Mind perception. In S. T. Fiske, D. T. Gilbert, & G. Lindzey (Eds.), *The handbook of social psychology* (5th ed., pp. 498–541). New York, NY: Wiley.

Epstein, S. L. (2015). Wanted: collaborative intelligence. *Artificial Intelligence*, *221*, 36-45.

Eyal, P., David, R., Andrew, G., Zak, E., & Ekaterina, D. (2022). Data quality of platforms and panels for online behavioral research. *Behavior Research Methods*, *54*, 1643–1662.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149-1160.

Fazio, R. H., Jackson, J. R., Dunton, B. C., & Williams, C. J. (1995). Variability in automatic activation as an unobtrusive measure of racial attitudes: A bona fide pipeline?. *Journal of Personality and Social Psychology*, *69*(6), 1013-1027.

Fazio, R. H., Sanbonmatsu, D. M., Powell, M. C., & Kardes, F. R. (1986). On the automatic activation of attitudes. *Journal of Personality and Social Psychology*, *50*(2), 229-238.

Fenwick, A., & Molnar, G. (2022). The importance of humanizing AI: using a behavioral lens to bridge the gaps between humans and machines. *Discover Artificial Intelligence*, *2*(1), 14.

Ferràs-Hernández, X. (2018). The future of management in a world of electronic brains. *Journal of Management Inquiry*, *27*(2), 260–263.

Field, A. (2013). *Discovering statistics using IBM SPSS statistics*. Sage.

Figoli, F. A., Rampino, L., & Mattioli, F. (2022). AI in design idea development: A workshop on creativity and human-AI collaboration. In *Proceedings of the DRS2022 Conference*.

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention, and behavior: An introduction to theory and research. *Addison-Wesley.*

Forgan, B. (2020, October 1). What robots can do for retail. *Harvard Business Review.* https://hbr.org/2020/10/what-robots-can-do-for-retail

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.

Fu, Q. Y., Chui, Y. P., & Helander, M. G. (2006). Knowledge identification and management in product design. *Journal of Knowledge Management*, *10*(6), 50-63.

Fuchs, C., Prandelli, E., Schreier, M., & Dahl, D. W. (2013). All that is users might not be gold: How labeling products as user designed backfires in the context of luxury fashion brands. *Journal of Marketing*, *77*(5), 75-91.

Gao, F., Agrawal, V. V., & Cui, S. (2022). The effect of multichannel and omnichannel retailing on physical stores. *Management Science*, *68*(2), 809-826.

Gao, Y., & Liu, H. (2022). Artificial intelligence-enabled personalization in interactive marketing: a customer journey perspective. *Journal of Research in Interactive Marketing*, (ahead-of-print), 1-18.

Gardner, M. P. (1985). Does attitude toward the ad affect brand attitude under a brand evaluation set?. *Journal of Marketing Research*, *22*(2), 192-198.

Gaube, S., Suresh, H., Raue, M., Merritt, A., Berkowitz, S. J., Lermer, E., ... & Ghassemi, M. (2021). Do as AI say: susceptibility in deployment of clinical decision-aids. *NPJ Digital Medicine*, *4*(1), 31.

Gauri, D. K., Jindal, R. P., Ratchford, B., Fox, E., Bhatnagar, A., Pandey, A., ... & Howerton, E. (2021). Evolution of retail formats: Past, present, and future. *Journal of Retailing*, *97*(1), 42-61.

Gerbing, D. W., & Anderson, J. C. (1992). Monte Carlo evaluations of goodness of fit indices for structural equation models. *Sociological Methods & Research*, *21*(2), 132-160.

Geuens, M., & De Pelsmacker, P. (2017). Planning and conducting experimental advertising research and questionnaire design. *Journal of Advertising*, *46*(1), 83-100.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2020). Generative adversarial networks. *Communications of the ACM*, *63*(11), 139-144.

Granger, M. M. (2015). *The fashion industry and its careers: An introduction*. Bloomsbury Publishing USA.

Granulo, A., Fuchs, C., & Puntoni, S. (2021). Preference for human (vs. robotic) labor is stronger in symbolic consumption contexts. *Journal of Consumer Psychology*, *31*(1), 72-80.

Gray, H. M., Gray, K., & Wegner, D. M. (2007). Dimensions of mind perception. *Science*, *315*(5812), 619-619.

Gray, K., & Wegner, D. M. (2012). Feeling robots and human zombies: Mind perception and the uncanny valley. *Cognition*, *125*(1), 125-130.

Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. (1998). Measuring individual differences in implicit cognition: the implicit association test. *Journal of Personality and Social Psychology*, *74*(6), 1464-1480.

Guha, A., Grewal, D., Kopalle, P. K., Haenlein, M., Schneider, M. J., Jung, H., ... & Hawkins, G. (2021). How artificial intelligence will affect the future of retailing. *Journal of Retailing*, *97*(1), 28-41.

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, *61*(4), 5-14.

Hair, J. F., Black, W. C., Anderson, R. E., & Babin, B. J. (2019). *Multivariate data analysis.* (8th ed.). London: Cengage Learning.

Han, S., & Koo, H. S. (2014). Anti-theft travel bag design: advantage, interest, and satisfaction. *International Journal of Fashion Design, Technology and Education*, *7*(3), 144-153.

Harreis, H., Koullias, T., Roberts, R., & Te, K. (2023, March 8). Generative AI: Unlocking the future of fashion. *McKinsey & Company.* https://www.mckinsey.com/industries/retail/our-insights/generative-ai-unlocking-the-future-of-fashion

Harrington, D. (2009). *Confirmatory factor analysis*. Oxford university press.

Hasan, R., Shams, R., & Rahman, M. (2021). Consumer trust and perceived risk for voice-controlled artificial intelligence: The case of Siri. *Journal of Business Research*, *131*, 591-597.

Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford publications.

He, D., Melumad, S., & Pham, M. T. (2019). The pleasure of assessing and expressing our likes and dislikes. *Journal of Consumer Research*, *46*(3), 545-563.

Helfrich, T. (2022, August 12). 10 ways to use AI for a successful product launch. *Forbes*. https://www.forbes.com/sites/forbestechcouncil/2022/08/12/10-ways-to-use-ai-for-a-successful-product-launch/?sh=1d5ace9874b1

Hirschman, E. C., & Holbrook, M. B. (1982). Hedonic consumption: emerging concepts, methods and propositions. *Journal of Marketing*, *46*(3), 92-101.

Hoffman, D. L., Moreau, C. P., Stremersch, S., & Wedel, M. (2022). The rise of new technologies in marketing: a framework and outlook. *Journal of Marketing*, *86*(1), 1-6.

Hollins, B., & Pugh, S. (1990). *Successful product design: what to do and when*. Butterworth-Heinemann.

Hong, J. W. (2018, July). Bias in perception of art produced by artificial intelligence. In *International Conference on Human-Computer Interaction* (pp. 290-303). Springer, Cham.

Hong, J. W., & Curran, N. M. (2019). Artificial intelligence, artists, and art: attitudes toward artwork produced by humans vs. artificial intelligence. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, *15*(2s), 1-16.

Hong, J. W., Fischer, K., Ha, Y., & Zeng, Y. (2022). Human, I wrote a song for you: An experiment testing the influence of machines' attributes on the AI-composed music evaluation. *Computers in Human Behavior*, *131*, 107239.

Hopkin, G. (2023, January 17). Human-AI hybrid designers to produce fashions of the future. *AI Magazine.* https://aimagazine.com/articles/human-ai-hybrid-designers-to-produce-fashions-of-the-future

Hopkins, J. (2021). *Fashion Design: The Complete Guide*. Bloomsbury Publishing.

Hsieh, H. Y. (2014, June). The influence of the designer's expertise on emotional responses. *International Conference on Human Interface and the Management of Information* (pp. 572-582). Springer, Cham.

Hu, L. T., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods*, *3*(4), 424-453.

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, *21*(2), 155-172.

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, *49*(1), 30-50.

Huang, M. H., & Rust, R. T. (2022). A framework for collaborative artificial intelligence in marketing. *Journal of Retailing*, *98*(2), 209-223.

Huang, Y. S. S., & Dootson, P. (2022). Chatbots and service failure: When does it lead to customer aggression. *Journal of Retailing and Consumer Services*, *68*, 103044.

Huh, J., Kim, H. Y., & Lee, G. (2023). "Oh, happy day!" Examining the role of AI-powered voice assistants as a positive technology in the formation of brand loyalty. *Journal of Research in Interactive Marketing*.

Huh, J., Whang, C., & Kim, H. Y. (2023). Building trust with voice assistants for apparel shopping: The effects of social role and user autonomy. *Journal of Global Fashion Marketing*, *14*(1), 5-19.

Hulland, J., & Miller, J. (2018). "Keep on turkin'"?. *Journal of the Academy of Marketing Science*, *46*, 789-794.

Im, H., & Lee, G. (2023). Do consumers always believe humans create better boxes than AI? The context-dependent role of recommender creativity. *International Journal of Retail & Distribution Management*.

Jin, B., Almousa, M. O., Yang, H., & Kim, N. (2018). Differential effects of macro and micro country images by product category and by country among Saudi consumers. *Management Decision*, *56*(8), 1663-1681.

Johnson, K., Lennon, S. J., & Rudd, N. (2014). Dress, body and self: Research in the social psychology of dress. *Fashion and Textiles*, *1*(1), 1-24.

Jung, J., & Lee, Y. J. (2009). Cross-cultural examination of women's fashion and beauty magazine advertisements in the United States and South Korea. *Clothing and Textiles Research Journal*, *27*(4), 274-286.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15-25.

Kees, J., Berry, C., Burton, S., & Sheehan, K. (2017). An analysis of data quality: Professional panels, student subject pools, and Amazon's Mechanical Turk. *Journal of Advertising*, *46*(1), 141-155.

Khasawneh, O. Y. (2018). Technophobia: Examining its hidden factors and defining it. *Technology in Society*, *54*, 93-100.

Kim, M., Huang, R., & Lennon, S. J. (2022, December). Understanding the role of cognitive and affective trust in consumer-artificial intelligence relationships. *International Textile and Apparel Association Annual Conference Proceedings, USA, 79*(1).

Kirk, R. E. (2012). *Experimental design: Procedures for the behavioral sciences*. Sage Publications.

Kirkpatrick, A. W., Hmielowski, J. D., & Boyd, A. D. (2022). The Indirect Effects of Episodic-Thematic Framing on Information Sharing About the Economic Threat of Artificial Intelligence. *Communication Studies*, *73*(5-6), 577-590.

Knuth, T., & Ahrholdt, D. C. (2022). Consumer fraud in online Shopping: detecting risk indicators through data mining. *International Journal of Electronic Commerce*, *26*(3), 388-411.

Koo, S. H. (2018). Design factors and preferences in wearable soft robots for movement disabilities. *International Journal of Clothing Science and Technology*, *30*(4), 477-495.

Kumar, V., Ramachandran, D., & Kumar, B. (2021). Influence of new-age technologies on marketing: A research agenda. *Journal of Business Research*, *125*, 864-877.

Kurilla, B. (2015). Analyzing analysis of variance: Violation of assumptions. *Geek Psychologist.* https://geekpsychologist.com/analyzing-analysis-of-variance-violation-of-assumptions/

Lamb, J. M., & Kallal, M. J. (1992). A conceptual framework for apparel design. *Clothing and Textiles Research Journal*, *10*(2), 42-47.

Lawson, B., & Dorst, K. (2013). *Design expertise*. Routledge.

Lee, J., Ko, E., & Megehee, C. M. (2015). Social benefits of brand logos in presentation of self in cross and same gender influence contexts. *Journal of Business Research*, *68*(6), 1341-1349.

Lee, M., Lucas, G., Mell, J., Johnson, E., & Gratch, J. (2019, July). What's on your virtual mind? Mind perception in human-agent negotiations. *In Proceedings of the 19th ACM international conference on intelligent virtual agents* (pp. 38-45).

Lee, S., Lee, N., & Sah, Y. J. (2020). Perceiving a mind in a chatbot: Effect of mind perception and social cues on co-presence, closeness, and intention to use. *International Journal of Human–Computer Interaction*, *36*(10), 930-940.

Lee, Y. K. (2022). How complex systems get engaged in fashion design creation: Using artificial intelligence. *Thinking Skills and Creativity*, *46*, 101137.

Lennon, S. J., Johnson, K. K. P., & Rudd, N. A. (2017). *The social psychology of dress*. Fairchild Bloomsbury.

Lesher, J. H. (1992). *Xenophanes of Colophon: Fragments*. Toronto: University of Toronto Press.

Li, H., & Lachmayer, R. (2018, August). Generative design approach for modeling creative designs. In *IOP Conference Series: Materials Science and Engineering* (Vol. 408, No. 1, p. 012035). IOP Publishing.

Liao, J., Hansen, P., & Chai, C. (2020). A framework of artificial intelligence augmented design support. *Human–Computer Interaction*, *35*(5-6), 511-544.

Libai, B., Bart, Y., Gensler, S., Hofacker, C. F., Kaplan, A., Kötterheinrich, K., & Kroll, E. B. (2020). Brave new world? On AI and the management of customer relationships. *Journal of Interactive Marketing*, *51*, 44-56.

Lima, G., Zhunis, A., Manovich, L., & Cha, M. (2021). On the social-relational moral standing of AI: an empirical study using AI-generated art. *Frontiers in Robotics and AI*, *8*. 719944.

Lin, M., Cui, X., Wang, J., Wu, G., & Lin, J. (2022). Promotors or inhibitors? Role of task type on the effect of humanoid service robots on consumers' use intention. *Journal of Hospitality Marketing & Management*, *31*(6), 710-729.

Lin, Y. C., & Chang, C. C. A. (2021). Influencing consumer responses to highly aesthetic products: the role of mindsets. *Journal of Retailing*, *97*(3), 459-476.

Lo, A., & Yeung, M. A. (2020). Brand prestige and affordable luxury: The role of hotel guest experiences. *Journal of Vacation Marketing*, *26*(2), 247-267.

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, *151*, 90-103.

Longoni, C., & Cian, L. (2022). Artificial intelligence in utilitarian vs. hedonic contexts: The "word-of-machine" effect. *Journal of Marketing*, *86*(1), 91-108.

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research*, *46*(4), 629-650.

Lopez, C. E., Miller, S. R., & Tucker, C. S. (2019). Exploring biases between human and machine generated designs. *Journal of Mechanical Design*, *141*(2), 021104.

Loske, D., & Klumpp, M. (2021). Human-AI collaboration in route planning: An empirical efficiency-based analysis in retail logistics. *International Journal of Production Economics*, *241*, 108236.

Lou, C., Kang, H., & Tse, C. H. (2022). Bots vs. humans: how schema congruity, contingency-based interactivity, and sympathy influence consumer perceptions and patronage intentions. *International Journal of Advertising*, *41*(4), 655-684.

Loureiro, S. M. C., Ashfaq, M., & Rodrigues, M. O. B. (2021). AI Meaning and Applications in the Consumer Sector of Retailing, Hospitality, and Tourism. In *Handbook of Research on Applied Data Science and Artificial Intelligence in Business and Industry* (pp. 291-303). IGI Global.

Luo, X., Qin, M. S., Fang, Z., & Qu, Z. (2021). Artificial intelligence coaches for sales agents: Caveats and solutions. *Journal of Marketing*, *85*(2), 14-32.

Marchand, A., & Marx, P. (2020). Automated product recommendations with preference-based explanations. *Journal of Retailing*, *96*(3), 328-343.

Mariani, M. M., Hashemi, N., & Wirtz, J. (2023). Artificial intelligence empowered conversational agents: A systematic literature review and research agenda. *Journal of Business Research*, *161*, 113838.

Marks, L. J., & Kamins, M. A. (1988). The use of product sampling and advertising: Effects of sequence of exposure and degree of advertising claim exaggeration on

consumers' belief strength, belief confidence, and attitudes. *Journal of Marketing Research*, *25*(3), 266-281.

Mason, O. J., Stevenson, C., & Freedman, F. (2014). Ever-present threats from information technology: the Cyber-Paranoia and Fear Scale. *Frontiers in Psychology*, *5*, 1298.

McCarthy, J. (2007, November 12). *What is artificial intelligence?* Computer Science Department Stanford University. http://www-formal.stanford.edu/jmc/whatisai.pdf.

Mellers, B. A., Lu, L., & McCoy, J. P. (2023). Predicting the future with humans and AI. *Consumer Psychology Review*, *6*(1), 109-120.

Menidjel, C., Hollebeek, L. D., Leppiman, A., & Riivits-Arkonsuo, I. (2022). Role of AI in enhancing customer engagement, loyalty and loyalty programme performance. In *Handbook of Research on Customer Loyalty* (pp. 316-331). Edward Elgar Publishing.

Millan, E., & Reynolds, J. (2014). Self-construals, symbolic and hedonic preferences, and actual purchase behavior. *Journal of Retailing and Consumer Services*, *21*(4), 550-560.

Missaoui, S., Gutierrez-Lopez, M., MacFarlane, A., Makri, S., Porlezza, C., & Cooper, G. (2019). How to blend journalistic expertise with artificial intelligence for research and verifying news stories. *CHI 2019 ACM Conference on Human Factors in Computing Systems*.

MIT Technology Review Insights. (2021, May 10). Product design gets an AI makeover. *MIT Technology Review*. https://www.technologyreview.com/2021/05/10/1024531/product-design-gets-an-ai-makeover/

Mitchell, A. A. (1986). The effect of verbal and visual components of advertisements on brand attitudes and attitude toward the advertisement. *Journal of Consumer Research*, *13*(1), 12-24.

Mitchell, A. A., & Olson, J. C. (1981). Are product attribute beliefs the only mediator of advertising effects on brand attitude? *Journal of Marketing Research*, *18*(3), 318-332.

Moffat, D. C., & Kelly, M. (2006). An investigation into people's bias against computational creativity in music composition. *Assessment*, *13*(11), 1-8.

Morgan, C., & Townsend, C. (2022). Why the drive: The utilitarian and hedonic benefits of self-expression through consumption. *Current Opinion in Psychology*, 101320.

Mozafari, N., Weiger, W. H., & Hammerschmidt, M. (2022). Trust me, I'm a bot–repercussions of chatbot disclosure in different service frontline settings. *Journal of Service Management*, *33*(2), 221-245.

Murphy, K. P. (2022). *Probabilistic machine learning: an introduction*. MIT press.

Nelissen, R. M., & Meijers, M. H. (2011). Social benefits of luxury brands as costly signals of wealth and status. *Evolution and Human Behavior*, *32*(5), 343-355.

Neslin, S. A. (2022). The omnichannel continuum: Integrating online and offline channels along the customer journey. *Journal of Retailing*, *98*(1), 111-132.

Noble, S. M., Mende, M., Grewal, D., & Parasuraman, A. (2022). The Fifth Industrial Revolution: How harmonious human–machine collaboration is triggering a retail and service [r]evolution. *Journal of Retailing*, *98*(2), 199-208.

Nosek, B. A., Greenwald, A. G., & Banaji, M. R. (2007). The Implicit Association Test at age 7: A methodological and conceptual review. In J. A. Bargh (Ed.), *Social psychology and the unconscious: The automaticity of higher mental processes* (pp. 265–292). New York: Psychology Press.

Nozawa, C., Togawa, T., Velasco, C., & Motoki, K. (2022). Consumer responses to the use of artificial intelligence in luxury and non-luxury restaurants. *Food Quality and Preference*, *96*, 104436.

Nunes, J. C., Hsee, C. K., & Weber, E. U. (2004). Why are people so prone to steal software? The effect of cost structure on consumer purchase and payment intentions. *Journal of Public Policy & Marketing*, *23*(1), 43-53.

O'cass, A. (2004). Fashion clothing consumption: antecedents and consequences of fashion clothing involvement. *European journal of Marketing*, *38*(7), 869-882.

Oh, C., Lee, T., Kim, Y., Park, S., Kwon, S., & Suh, B. (2017). Us vs. them: Understanding artificial intelligence technophobia over the google deepmind challenge match. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, 2523-2534.

Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research*, *17*(4), 460-469.

Page, K. L., & Uncles, M. D. (2014). The complexity of surveying web participation. *Journal of Business Research*, *67*(11), 2356-2367.

Pan, Y., & Froese, F. J. (2023). An interdisciplinary review of AI and HRM: Challenges and future directions. *Human Resource Management Review*, 100924.

Papagiannis, H. (2020, January 22). Acne Studios X Robbie Barrat. *XR Goes Pop*. https://xrgoespop.com/home/acne-studios-x-robbie-barrat

Park, H., Park, J., Lin, S. H., & Boorady, L. M. (2014). Assessment of Firefighters' needs for personal protective equipment. *Fashion and Textiles*, *1*(1), 1-13.

Park, M., Im, H., & Kim, H. Y. (2020). "You are too friendly!" The negative effects of social media marketing on value perceptions of luxury fashion brands. *Journal of Business Research*, *117*, 529-542.

Park, S. S., Tung, C. D., & Lee, H. (2021). The adoption of AI service robots: A comparison between credence and experience service settings. *Psychology & Marketing*, *38*(4), 691-703.

Payne, E. H. M., Peltier, J., & Barger, V. A. (2021). Enhancing the value co-creation process: artificial intelligence and mobile banking service platforms. *Journal of Research in Interactive Marketing*, *15*(1), 68-85.

Pedersen, C. L. (2021). Empathy-based marketing. *Psychology & Marketing*, *38*(3), 470-480.

Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *Journal of Experimental Social Psychology*, *70*, 153-163.

Peng, C., van Doorn, J., Eggers, F., & Wieringa, J. E. (2022). The effect of required warmth on consumer acceptance of artificial intelligence in service: The moderating role of AI-human collaboration. *International Journal of Information Management*, *66*, 102533.

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of Management*, *12*(4), 531-544.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879-903.

Popovic, V. (2004). Expertise development in product design—strategic and domain-specific knowledge connections. *Design Studies*, *25*(5), 527-545.

Precedence Research. (2023, January). Artificial Intelligence (AI) market size, growth, report 2022-2030. https://www.precedenceresearch.com/artificial-intelligence-market

Premack, D., & Woodruff, G. (1978). Does the chimpanzee have a theory of mind?. *Behavioral and Brain Sciences*, *1*(4), 515-526.

Qin, X., & Jiang, Z. (2019). The impact of AI on the advertising process: The Chinese experience. *Journal of Advertising*, *48*(4), 338-346.

Ragot, M., Martin, N., & Cojean, S. (2020, April). AI-generated vs. human artworks. a perception bias towards artificial intelligence?. In *Extended abstracts of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1-10).

Raj, M., Berg, J., and Seamans, R. (2023). Artificial Intelligence: The effect of AI disclosure on evaluations of creative content. *SSRN Working Paper.*

Ratcliff, R., & Hendrickson, A. T. (2021). Do data from mechanical Turk subjects replicate accuracy, response time, and diffusion modeling results?. *Behavior Research Methods*, *53*(6), 2302-2325.

Ratneshwar, S., & Chaiken, S. (1991). Comprehension's role in persuasion: The case of its moderating effect on the persuasive impact of source cues. *Journal of Consumer Research*, *18*(1), 52-62.

Rifkin, J. R., Du, K. M., & Berger, J. (2021). Penny for your preferences: leveraging self-expression to encourage small prosocial gifts. *Journal of Marketing*, *85*(3), 204-219.

Rodgers, S. (2021). Themed issue introduction: Promises and perils of artificial intelligence and advertising. *Journal of Advertising*, *50*(1), 1-10.

Roose, K. (2022, September 2). An A.I.-generated picture won an art prize. Artists aren't happy. *The New York Times.* https://www.nytimes.com/2022/09/02/technology/ai-artificial-intelligence-artists.html

Rosen, L. D., & Weil, M. M. (1995). Computer availability, computer experience and technophobia among public school teachers. *Computers in human behavior*, *11*(1), 9-31.

Ruan, Y., & Mezei, J. (2022). When do AI chatbots lead to higher customer satisfaction than human frontline employees in online shopping assistance? Considering product attribute type. *Journal of Retailing and Consumer Services*, *68*, 103059.

Russell, S. J. (2010). *Artificial intelligence a modern approach*. Pearson Education, Inc.

Rust, R. T., & Huang, M. H. (2021). *The feeling economy: How artificial intelligence is creating the era of empathy*. Cham, Switzerland: Palgrave Macmillan.

Ryan, T. (2021, March 1). Automated checkout 'will be everywhere' sooner rather than later. *RetailWire.* https://retailwire.com/discussion/automated-checkout-will-be-everywhere-sooner-rather-than-later/

Schlosser, A. E., White, T. B., & Lloyd, S. M. (2006). Converting web site visitors into buyers: how web site investment increases consumer trusting beliefs and online purchase intentions. *Journal of Marketing*, *70*(2), 133-148.

Schneider, L. P., & Cornwell, T. B. (2005). Cashing in on crashes via brand placement in computer games: The effects of experience and flow on memory. *International Journal of Advertising*, *24*(3), 321-343.

Schreier, M., Fuchs, C., & Dahl, D. W. (2012). The innovation effect of user design: Exploring consumers' innovation perceptions of firms selling products designed by users. *Journal of Marketing*, *76*(5), 18-32.

Segijn, C. M., Opree, S. J., & van Ooijen, I. (2022). The validation of the perceived surveillance scale. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, *16*(3), 9.

Sen, M. (2017, June 5). These unique Nutella jars completely sold out in Italy. *Insider*. https://www.businessinsider.com/nutella-unica-jars-in-italy-2017-6?IR=T

Sen, S., & Lerman, D. (2007). Why are you telling me this? An examination into negative consumer reviews on the web. *Journal of Interactive Marketing*, *21*(4), 76-94.

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Houghton, Mifflin and Company.

Shankar, V. (2018). How artificial intelligence (AI) is reshaping retailing. *Journal of Retailing*, *94*(4), vi-xi.

Shankar, V., Kalyanam, K., Setia, P., Golmohammadi, A., Tirunillai, S., Douglass, T., ... & Waddoups, R. (2021). How technology is changing retail. *Journal of Retailing*, *97*(1), 13-27.

Shin, J., & Lee, S. (2020, January). Intimacy between actual users and virtual agents: Interaction through "likes" and "comments". In *2020 14th International Conference on Ubiquitous Information Management and Communication (IMCOM)* (pp. 1-4). IEEE.

Shirer, M. (2022, March 17). *Spending on Artificial Intelligence Solutions Will Double in the United States by 2025, According to a New IDC Spending Guide*. IDC. https://www.idc.com/getdoc.jsp?containerId=prUS48958822

Sim, M., Kim, S. Y., & Suh, Y. (2022). Sample size requirements for simple and complex mediation models. *Educational and Psychological Measurement*, *82*(1), 76-106.

Smith, L. W., Rose, R. L., Zablah, A. R., McCullough, H., & Saljoughian, M. M. (2022). Examining post-purchase consumer responses to product automation. *Journal of the Academy of Marketing Science*, *51*, 530-550.

Smith, S. (2022, December 30). How to use automation for your ecommerce website? *Digital Marketing Blog*. https://www.spiderseocompany.com/2022/12/30/how-to-use-automation-for-your-ecommerce-website/

Söderlund, M. (2022). Service robots with (perceived) theory of mind: An examination of humans' reactions. *Journal of Retailing and Consumer Services*, *67*, 102999.

Söderlund, M., & Oikarinen, E. L. (2021). Service encounters with virtual agents: an examination of perceived humanness as a source of customer satisfaction. *European Journal of Marketing*, *55*(13), 94-121.

Sohn, K., Sung, C. E., Koo, G., & Kwon, O. (2020). Artificial intelligence in the fashion industry: consumer responses to generative adversarial network (GAN) technology. *International Journal of Retail & Distribution Management*, *49*(1), 61-80.

Song, C. S., & Kim, Y. K. (2022). The role of the human-robot interaction in consumers' acceptance of humanoid retail service robots. *Journal of Business Research*, *146*, 489-503.

Spirling, A. (2023, April 18). Why open-source generative AI models are an ethical way forward for science. *Nature*. https://www.nature.com/articles/d41586-023-01295-4

Srinivasan, R., & Sarial-Abi, G. (2021). When algorithms fail: Consumers' responses to brand harm crises caused by algorithm errors. *Journal of Marketing*, *85*(5), 74-91.

Steiger, J. H., & Lind, J. C. (1980). Statistically Based Tests for the Number of Common Factors. Paper Presented at the Psychometric Society Annual Meeting, Iowa City, IA.

Steinhart, Y., Kamins, M., Mazursky, D., & Noy, A. (2014). Effects of product type and contextual cues on eliciting naive theories of popularity and exclusivity. *Journal of Consumer Psychology*, *24*(4), 472-483.

Sun, D., Wang, H., & Xiong, J. (2023). Would you like to listen to my music, my friend? An experiment on AI musicians. *International Journal of Human–Computer Interaction*, 1-11.

Sung, E. C., Bae, S., Han, D. I. D., & Kwon, O. (2021). Consumer engagement via interactive artificial intelligence and mixed reality. *International Journal of Information Management*, *60*, 102382.

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics* (5th ed.). Upper Saddle River, NJ: Pearson Allyn & Bacon.

Takahashi, H., Ban, M., & Asada, M. (2016). Semantic differential scale method can reveal multi-dimensional aspects of mind perception. *Frontiers in psychology*, *7*, 1717.

Tharp, M., Holtzman, N. S., & Eadeh, F. R. (2017). Mind perception and individual differences: A replication and extension. *Basic and Applied Social Psychology*, *39*(1), 68-73.

Thomas, V. L., & Fowler, K. (2021). Close encounters of the AI kind: Use of AI influencers as brand endorsers. *Journal of Advertising*, *50*(1), 11-25.

Thompson, B. (2004). *Exploratory and confirmatory factor analysis: Understanding concepts and applications.* Washington, DC: American Psychological Association.

Ting, J. (2022, February 19). Greedilous debuts first AI-designed collection at NYFW. *Paper Magazine.* https://www.papermag.com/greedilous-tilda-ai-nyfw-2022-2656729055.html?rebelltitem=3#rebelltitem3

Tran, A. D., Pallant, J. I., & Johnson, L. W. (2021). Exploring the impact of chatbots on consumer sentiment and expectations in retail. *Journal of Retailing and Consumer Services*, *63*, 102718.

Tucker, L. R., & Lewis, C. (1973). A reliability coefficient for maximum likelihood factor analysis. *Psychometrika*, *38*(1), 1-10.

van Esch, P., Cui, Y., & Jain, S. P. (2021a). Self-efficacy and callousness in consumer judgments of AI-enabled checkouts. *Psychology & Marketing*, *38*(7), 1081-1100.

van Esch, P., Cui, Y., & Jain, S. P. (2021b). Stimulating or intimidating: The effect of AI-enabled in-store communication on consumer patronage likelihood. *Journal of Advertising, 50*(1), 63-80.

Verganti, R., Vendraminelli, L., & Iansiti, M. (2020). Innovation and design in the age of artificial intelligence. *Journal of Product Innovation Management*, *37*(3), 212-227.

Wan, X., Wang, T., & Wu, J. (2018). I'll follow the minority: The effects of sales level on purchase intention of self-expressive products. *Frontiers in Psychology*, *9*, 1135.

Wang, J., & Wallendorf, M. (2006). Materialism, status signaling, and product satisfaction. *Journal of the Academy of Marketing Science*, *34*(4), 494-505.

Ward, M. K., & Dahl, D. W. (2014). Should the devil sell Prada? Retail rejection increases aspiring consumers' desire for the brand. *Journal of Consumer Research*, *41*(3), 590-609.

Waytz, A., Gray, K., Epley, N., & Wegner, D. M. (2010). Causes and consequences of mind perception. *Trends in Cognitive Sciences*, *14*(8), 383-388.

Waytz, A., Heafner, J., & Epley, N. (2014). The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle. *Journal of Experimental Social Psychology, 52*, 113-117.

Whang, C., & Im, H. (2021). "I like your suggestion!" The role of humanlikeness and parasocial relationship on the website versus voice shopper's perception of recommendations. *Psychology & Marketing*, *38*(4), 581-595.

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review*, *96*(4), 114-123.

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: service robots in the frontline. *Journal of Service Management, 29*(5), 907-931.

Wu, J., Xu, L., Yu, F., & Peng, K. (2021). Acceptance of medical treatment regimens provided by AI vs. human. *Applied Sciences, 12*(1), 110.

Wu, L., & Wen, T. J. (2021). Understanding AI advertising from the consumer perspective: What factors determine consumer appreciation of AI-created advertisements?. *Journal of Advertising Research*, *61*(2), 133-146.

Wu, L., Dodoo, N. A., Wen, T. J., & Ke, L. (2022). Understanding Twitter conversations about artificial intelligence in advertising based on natural language processing. *International Journal of Advertising*, *41*(4), 685-702.

Xia, L., Monroe, K. B., & Cox, J. L. (2004). The price is unfair! A conceptual framework of price fairness perceptions. *Journal of Marketing*, *68*(4), 1-15.

Xian, W., Sangkloy, P., Agrawal, V., Raj, A., Lu, J., Fang, C., ... & Hays, J. (2018). Texturegan: Controlling deep image synthesis with texture patches.

In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 8456-8465).

Xie, Z., Yu, Y., Zhang, J., & Chen, M. (2022). The searching artificial intelligence: Consumers show less aversion to algorithm-recommended search product. *Psychology & Marketing*, *39*(10), 1902-1919.

Xu, K., Liu, F., Mou, Y., Wu, Y., Zeng, J., & Schäfer, M. S. (2020). Using machine learning to learn machines: A cross-cultural study of users' responses to machine-generated artworks. *Journal of Broadcasting & Electronic Media, 64*(4), 566-591.

Xu, L., & Mehta, R. (2022). Technology devalues luxury? Exploring consumer responses to AI-designed luxury products. *Journal of the Academy of Marketing Science, 50*, 1135–1152.

Yam, K. C., Bigman, Y. E., Tang, P. M., Ilies, R., De Cremer, D., Soh, H., & Gray, K. (2021). Robots at work: People prefer—and forgive—service robots with perceived feelings. *Journal of Applied Psychology, 106*(10), 1557-1572.

Yam, K. C., Goh, E. Y., Fehr, R., Lee, R., Soh, H., & Gray, K. (2022). When your boss is a robot: Workers are more spiteful to robot supervisors that seem more human. *Journal of Experimental Social Psychology*, *102*, 104360.

Yam, K. C., Tang, P. M., Jackson, J. C., Su, R., & Gray, K. (2022). The rise of robots increases job insecurity and maladaptive workplace behaviors: Multimethod evidence. *Journal of Applied Psychology*, *108*(5), 850-870.

Yoo, J., & Park, M. (2016). The effects of e-mass customization on consumer perceived value, satisfaction, and loyalty toward luxury brands. *Journal of Business Research*, *69*(12), 5775-5784.

Young Entrepreneur Council. (2023, February 21). Artificial Intelligence in Fashion. *Forbes*. https://www.forbes.com/sites/theyec/2023/02/21/artificial-intelligence-in-fashion/?sh=61dca3e57adb

Yun, J. T., Segijn, C. M., Pearson, S., Malthouse, E. C., Konstan, J. A., & Shankar, V. (2020). Challenges and future directions of computational advertising measurement systems. *Journal of Advertising*, *49*(4), 446-458.

Zhang, H., Bai, X., & Ma, Z. (2022). Consumer reactions to AI design: Exploring consumer willingness to pay for AI-designed products. *Psychology & Marketing*, *39*(11), 2171-2183.

Zhang, H., Chen, Y., & Li, X. (2020). A note on exploratory item factor analysis by singular value decomposition. *Psychometrika*, *85*(2), 358-372.

Zhang, M., Gursoy, D., Zhu, Z., & Shi, S. (2021). Impact of anthropomorphic features of artificially intelligent service robots on consumer acceptance: moderating role of sense of humor. *International Journal of Contemporary Hospitality Management, 33*(11), 3883-3905.

Zhu, Y., Zhang, J., Wu, J., & Liu, Y. (2022). AI is better when I'm sure: The influence of certainty of needs on consumers' acceptance of AI chatbots. *Journal of Business Research, 150,* 642-652.

Zöller, S. (2019). *Mapping individual subjective values to product design: an attitudes-based approach for user centered design*. FAU University Press.

Appendix A. Study 1 Questionnaire

Introduction

You are invited to participate in the study of consumers' fashion consumption tendency. We appreciate your participation. A researcher of this study is Garim Lee, a graduate student in the Department of Design, Housing, and Apparel, College of Design, University of Minnesota. The faculty advisor of this research is Dr. Hye-Young Kim.

Procedures

If you agree to be in this study, you will be asked to carefully complete the survey. The survey will ask for your opinions about fashion products. It will take about **7-8 minutes to complete**.

Compensation

After completing the survey, you will get paid **$1.6** for participation. At the end of the survey, you will receive a code to paste into the box in the "Hit" to receive credit for taking our survey.

Confidentiality

The records of this study will be kept private. In any sort of report, we might publish, we will not include any information that will make it possible to identify a subject. Research records will be stored securely, and only researchers will have access to the records.

Voluntary Nature of the Study

Participation in this study is voluntary. Your decision whether or not to participate will not affect your current or future relations with the University of Minnesota. If you decide to participate, you are free to not answer any question or withdraw at any time without affecting those relationships.

Contacts and Questions

The researcher conducting this study is Garim Lee. You may ask any questions you have. If you have questions later, you are encouraged to contact the research by email (lee02169@umn.edu) or number (612-323-9833). If you have any questions or concerns regarding this study and would like to talk to someone other than the researcher, you are encouraged to contact the Research Participants' Advocate Line at 612-625-1650 (Toll Free: 1-888-224-8636) or go to https://research.umn.edu/units/hrpp/research- participants/questions-concerns.

Again, thank you for your interest in our study!

Do you live in the United States of America AND are you 18 years or older?
** If you indicate 'No', you will exit from the study.*

Yes

No

Please indicate whether you **“agree” or “disagree”** that you have read the information above and consented to participate in the study.
You can decline to participate or decide to terminate the survey at any time by simply closing your browser window.
** If you indicate 'Disagree', you will exit from the study.*

Agree

Disagree

→

Now, you will see **a scenario**.

Please read the scenario carefully as you will answer the questions based on the scenario.

→

Imagine that you are navigating the internet to find a fashionable jacket. You think it is important to find a jacket that reflects your self-image. When you click on the website of *KNIZZAZ*, you see exactly what you want in the brand's new arrival collection.

While reading the product description, you learn that the jacket was designed by algorithm-based Artificial Intelligence (AI). You feel the jacket is reasonably priced.

→

Through the scenario, you imagined that you saw a fashion product. Please indicate the extent to which the entity **who designed the product was more like a computer system or a person.**

Very machine-like, more like a computer system	○ ○ ○ ○ ○ ○ ○	Very human-like, more like a person

→

In your opinion, is **the fashionable jacket** given in the scenario focusing on a **self-expressive attribute** or **functional attribute**? Please check off the circle below, with the left side representing self-expressive attributes more, and the right side representing functional attributes more.

- **Self-expressive attributes** are typically associated with the value to express something about one's personality or beliefs.
- **Functional attributes** are typically associated with the practical and pragmatic value of the product for specific purposes.

In my opinion, the fashionable jacket is...

Highly self-expressive	○ ○ ○ ○ ○ ○ ○	Highly functional

→

Please indicate **how much you agree with each statement about the fashionable jacket you want** in the scenario.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
The fashionable jacket can tell others what kind of person the owner is.	○	○	○	○	○	○	○
The fashionable jacket can shape the owner's image in the eyes of others.	○	○	○	○	○	○	○
The fashionable jacket can convey one's personality to the people around him/her.	○	○	○	○	○	○	○
The fashionable jacket can reflect the owner's identity.	○	○	○	○	○	○	○

→

In your opinion, how much is **algorithm-based AI capable of the following?**

	Not at all			Somewhat			Very much
Experiencing physical or emotional pleasure	○	○	○	○	○	○	○

Feeling hungry	○	○	○	○	○	○	○
Experiencing violent and uncontrolled anger	○	○	○	○	○	○	○
Longing or hoping for things	○	○	○	○	○	○	○
	Not at all			Somewhat			Very much
Having personality traits	○	○	○	○	○	○	○
Experiencing pride	○	○	○	○	○	○	○
Feeling afraid or fearful	○	○	○	○	○	○	○
Having experiences and being aware of things	○	○	○	○	○	○	○
	Not at all			Somewhat			Very much
Experiencing embarrassment	○	○	○	○	○	○	○
Experiencing physical or emotional pain	○	○	○	○	○	○	○
Experiencing joy	○	○	○	○	○	○	○

→

In your opinion, how much is **algorithm-based AI capable of the following?**

	Not at all			Somewhat			Very much
Exercising self-restraint over impulses	○	○	○	○	○	○	○
Remembering things	○	○	○	○	○	○	○
Thinking	○	○	○	○	○	○	○
Telling right from wrong	○	○	○	○	○	○	○

	Not at all			Somewhat			Very much
Understanding how others feel	○	○	○	○	○	○	○
Making plans	○	○	○	○	○	○	○
Conveying thoughts to others	○	○	○	○	○	○	○

→

Please indicate how much **you agree with each statement about algorithm-based AI**.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
In my opinion, algorithm-based AI has the competence to design new fashion products.	○	○	○	○	○	○	○
In my opinion, algorithm-based AI has the necessary skills (know-how) to design new products.	○	○	○	○	○	○	○
In my opinion, algorithm-based AI has very high design expertise.	○	○	○	○	○	○	○

→

How would you rate the fashionable jacket designed by AI you just saw in the scenario, on each of the following attributes?

bad	○	○	○	○	○	○	○	good
negative	○	○	○	○	○	○	○	positive
unfavorable	○	○	○	○	○	○	○	favorable
dislikable	○	○	○	○	○	○	○	likable
unappealing	○	○	○	○	○	○	○	appealing

→

Please answer the following questions about **the fashionable jacket designed by AI you just saw in the scenario.**

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I am likely to purchase this product.	○	○	○	○	○	○	○
I have a high intention to purchase this product.	○	○	○	○	○	○	○
I have a strong possibility to purchase this product.	○	○	○	○	○	○	○

→

How would you rate the brand *'KNIZZAZ'* you saw in the scenario, on each of the following attributes?

bad	○	○	○	○	○	○	○	good
unfavorable	○	○	○	○	○	○	○	favorable
dislikable	○	○	○	○	○	○	○	likable
negative	○	○	○	○	○	○	○	positive

→

How likely do you think it is that a scenario you just read about **would happen to you in real life?**

Totally unlikely ○ ○ ○ ○ ○ ○ ○ Totally likely

Through the scenario, you imagined that you saw a fashion product. **What was the fashion product?**

- Handbag
- Bracelet
- Jacket
- I don't know

Through the scenario, you imagined that you saw a fashion product. **Who designed the clothing item in the scenario?**

- Algorithm-based AI
- Award-winning designer
- I don't know

Through the scenario, you imagined that you saw a fashion product from a brand. **What was the brand name?**

- Zapprises Co.

Ladidian

Knizzaz

I don't know

→

Now, this section is about **your general opinions/tendencies**.

Please answer the questions carefully, but please do not think too much. There are no right or wrong answers. We are interested in your immediate, first responses to the questions.

→

Please rate the extent to which you perceive **Artificial intelligence (AI)** as **being threatening in general**.

* ***Note.*** *Artificial intelligence (AI) technology is a technological advancement that involves programming technology to problem solve.*

	Not at all			Somewhat			Very much
Challenged	○	○	○	○	○	○	○
Maligned	○	○	○	○	○	○	○
Impugned	○	○	○	○	○	○	○
Attacked	○	○	○	○	○	○	○

	Not at all			Somewhat			Very much
This is attention check. Please check "Not at all".	○	○	○	○	○	○	○

Unhappy	○	○	○	○	○	○	○
Threatened	○	○	○	○	○	○	○

→

Please indicate how much you agree or disagree with each statement below.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I am familiar with AI or AI content (texts, audiovisuals, etc.)	○	○	○	○	○	○	○
I have used AI-powered services or activities.	○	○	○	○	○	○	○
Throughout my life, I have had some experience with AI-powered services.	○	○	○	○	○	○	○

→

How would you rate **your experience with fashion design and/or designing products** in either a professional or unprofessional (e.g., as a hobby) capacity?

No experience	○	○	○	○	○	○	○	Many experience
Very little	○	○	○	○	○	○	○	Very much
Below average	○	○	○	○	○	○	○	Above average

→

Please indicate how much you agree with each statement below.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I find fashion clothing a very relevant product in my life.	○	○	○	○	○	○	○
I would say fashion clothing is central to my identity as a person.	○	○	○	○	○	○	○
Fashion clothing means a lot to me.	○	○	○	○	○	○	○
I am very much involved in / with fashion clothing.	○	○	○	○	○	○	○
For me personally fashion clothing is an important product.	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Fashion clothing is an important part of my life.	○	○	○	○	○	○	○
I can really identify with fashion clothing.	○	○	○	○	○	○	○

I have a very strong commitment to fashion clothing that would be difficult to break.	○	○	○	○	○	○	○
I am very interested in fashion clothing.	○	○	○	○	○	○	○
I would say that I am often preoccupied with fashion clothing.	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I think about fashion clothing a lot.	○	○	○	○	○	○	○
I consider fashion clothing to be a central part of my life.	○	○	○	○	○	○	○
I pay a lot of attention to fashion clothing.	○	○	○	○	○	○	○
Fashion clothing is important to me.	○	○	○	○	○	○	○

→

This is the last page of the survey questionnaire.

What is your age?

What is your gender?

- Male
- Female
- Other; Prefer not to answer

Which of the following best describes your ethnicity/race?

- Black, African, African American
- White / Caucasian
- Hispanic or Latino
- American Indian or Alaska native
- Native Hawaiian or other Pacific Islander
- Middle Eastern and North African
- Asian
- Other

What is the highest degree or level of school you have completed?

If you are currently enrolled, choose the highest degree received.
When you are currently in college, choose 'Some college, but no degree'.

- No schooling completed
- Elementary school
- High school or equivalent (e.g., GED)
- Some college, but no degree
- Associate's degree
- Bachelor's degree
- Master's degree
- Professional degree
- Doctoral degree
- Other

What is your marital status?

- Divorced
- Single
- Separated

Married

Widowed

Other; Prefer not to answer

Which of the following best describes your annual income?

Less than $25,000

$25,000 - $49,999

$50,000 - $74,999

$75,000 - $99,999

$100,000 or more

Which of the following options would best describe your job situation?

Retired

Unemployed

Part-time

Full-time

Other; Prefer not to answer

Appendix B. Study 2 Questionnaire

Introduction

You are invited to participate in the study of consumers' evaluation of a fashion product. We appreciate your participation. A researcher of this study is Garim Lee, a graduate student in the Department of Design, Housing, and Apparel, College of Design, University of Minnesota. The faculty advisor of this research is Dr. Hye-Young Kim.

Procedures

If you agree to be in this study, you will be asked to carefully complete the survey. The survey will ask for your opinions about fashion products. It will take about **7 minutes to complete**.

Compensation

After completing the survey, you will get paid **$1.6** for participation. At the end of the survey, you will receive a code to paste into the box in the "Hit" to receive credit for taking our survey.

Confidentiality

The records of this study will be kept private. In any sort of report, we might publish, we will not include any information that will make it possible to identify a subject. Research records will be stored securely, and only researchers will have access to the records.

Voluntary Nature of the Study

Participation in this study is voluntary. Your decision whether or not to participate will not affect your current or future relations with the University of Minnesota. If you decide to participate, you are free to not answer any question or withdraw at any time without affecting those relationships.

Contacts and Questions

The researcher conducting this study is Garim Lee. You may ask any questions you have. If you have questions later, you are encouraged to contact the research by email (lee02169@umn.edu). If you have any questions or concerns regarding this study and would like to talk to someone other than the researcher, you are encouraged to contact the Research Participants' Advocate Line at 612-625-1650 (Toll Free: 1-888-224-8636) or go to https://research.umn.edu/units/hrpp/research-participants/questions-concerns.

Again, thank you for your interest in our study!

Do you live in the United States of America AND are you 18 years or older?
** If you indicate 'No', you will exit from the study.*

Yes

No

Please indicate whether you **“agree” or “disagree”** that you have read the information above and consented to participate in the study.
You can decline to participate or decide to terminate the survey at any time by simply closing your browser window.
** If you indicate 'Disagree', you will exit from the study.*

Agree

Disagree

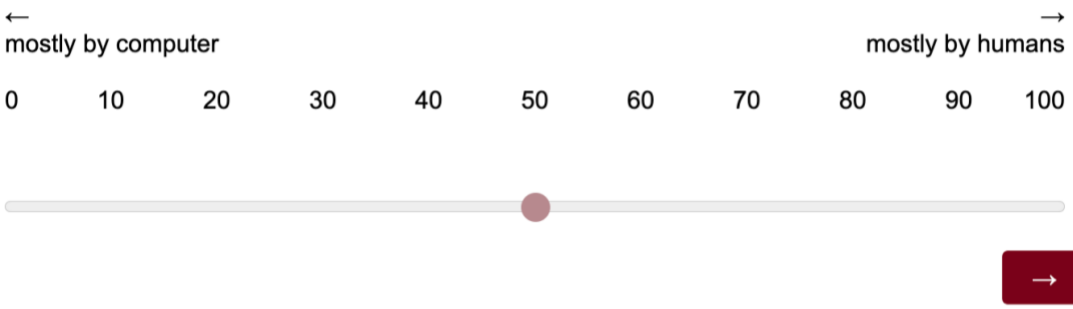
→

This sweater from the brand Knizzaz was designed by Artificial Intelligence (AI).

→

You saw **a sweater designed by AI.** Please indicate **the extent to which the product design process seemed more like**, based on the following description.

- **0 = mostly by computer.** The product was designed through an algorithm's automated processes.
- **50 =** by a **combination** of an algorithm's automation and human design processes.
- **100 = mostly by humans.** The product was designed through human design processes.



In your opinion, how much is **AI capable of the following?**

	Not at all			Somewhat			Very much
Having experiences and being aware of things	○	○	○	○	○	○	○
Experiencing joy	○	○	○	○	○	○	○
Experiencing physical or emotional pain	○	○	○	○	○	○	○
Experiencing embarrassment	○	○	○	○	○	○	○

	Not at all			Somewhat			Very much
Experiencing physical or emotional pleasure	○	○	○	○	○	○	○
Having personality traits	○	○	○	○	○	○	○

Feeling hungry	○	○	○	○	○	○	○
Feeling afraid or fearful	○	○	○	○	○	○	○
	Not at all			Somewhat			Very much
Longing or hoping for things	○	○	○	○	○	○	○
Experiencing pride	○	○	○	○	○	○	○
Experiencing violent and uncontrolled anger	○	○	○	○	○	○	○

→

In your opinion, how much is **AI capable of the following?**

	Not at all			Somewhat			Very much
Thinking	○	○	○	○	○	○	○
Telling right from wrong	○	○	○	○	○	○	○
Remembering things	○	○	○	○	○	○	○
Exercising self-restraint over impulses	○	○	○	○	○	○	○
	Not at all			Somewhat			Very much
Understanding how others feel	○	○	○	○	○	○	○
Making plans	○	○	○	○	○	○	○
Conveying thoughts to others	○	○	○	○	○	○	○

→

Please indicate how much **you agree with each statement about AI**.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
In my opinion, AI has the competence to design new fashion products.	○	○	○	○	○	○	○
In my opinion, AI has very high design expertise.	○	○	○	○	○	○	○
In my opinion, AI has the necessary skills (know-how) to design new products.	○	○	○	○	○	○	○

→

How would you rate the sweater designed by AI you just saw, on each of the following attributes?

"The sweater designed by AI is..."

negative	○ ○ ○ ○ ○ ○ ○	positive
dislikable	○ ○ ○ ○ ○ ○ ○	likable
bad	○ ○ ○ ○ ○ ○ ○	good
unfavorable	○ ○ ○ ○ ○ ○ ○	favorable
unappealing	○ ○ ○ ○ ○ ○ ○	appealing

→

Please answer the following questions about **the sweater designed by AI you just saw.**

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I am likely to purchase this product.	○	○	○	○	○	○	○
I have a high intention to purchase this product.	○	○	○	○	○	○	○
I have a strong possibility to purchase this product.	○	○	○	○	○	○	○

→

Please indicate how you think about **the brand *'KNIZZAZ'* you saw.**

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
The brand Knizzaz is positive.	○	○	○	○	○	○	○
The brand Knizzaz is good.	○	○	○	○	○	○	○
The brand Knizzaz is favorable.	○	○	○	○	○	○	○
The brand Knizzaz is likable.	○	○	○	○	○	○	○

→

You saw a fashion product. **What was the fashion product?**

- Handbag
- Sweater
- Bracelet
- I don't know

→

You saw a fashion product. **How was the product designed?**

- The product was designed by Artificial Intelligence.
- The product was designed by AI designer ‘Vella’.
- The product was designed through Human-AI collaboration.
- The product was designed through user collaboration.
- The product was designed by human designers.
- I don't know

→

You saw a fashion product from a brand. **What was the brand name?**

- Ladidian
- Zapprises Co.
- Knizzaz
- I don't know

→

Now, this section is about **your general opinions/tendencies**.

Please answer the questions carefully, but please do not think too much. There are no right or wrong answers. We are interested in your immediate, first responses to the questions.

→

Please rate the extent to which you perceive **Artificial intelligence (AI)** as **being threatening in general**.

* ***Note.*** *Artificial intelligence (AI) technology is a technological advancement that involves programming technology to problem solve.*

	Not at all			Somewhat			Very much
Challenged	○	○	○	○	○	○	○
Threatened	○	○	○	○	○	○	○
Maligned	○	○	○	○	○	○	○
Unhappy	○	○	○	○	○	○	○

Attacked	○	○	○	○	○	○	○
This is attention check. Please check "Not at all".	○	○	○	○	○	○	○
Impugned	○	○	○	○	○	○	○

→

Please indicate how much you agree or disagree with each statement below.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I am familiar with AI or AI content (texts, audiovisuals, etc.)	○	○	○	○	○	○	○
I have used AI-powered services or activities.	○	○	○	○	○	○	○
Throughout my life, I have had some experience with AI-powered services.	○	○	○	○	○	○	○

→

How would you rate **your experience with fashion design and/or designing products** in either a professional or unprofessional (e.g., as a hobby) capacity?

Below average	○	○	○	○	○	○	○	Above average
Very little	○	○	○	○	○	○	○	Very much
No experience	○	○	○	○	○	○	○	Many experience

→

Please indicate how much you agree with each statement below.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I think about fashion clothing a lot.	○	○	○	○	○	○	○
Fashion clothing means a lot to me.	○	○	○	○	○	○	○
For me personally fashion clothing is an important product.	○	○	○	○	○	○	○
I would say fashion clothing is central to my identity as a person.	○	○	○	○	○	○	○
Fashion clothing is important to me.	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I find fashion clothing a very relevant product in my life.	○	○	○	○	○	○	○
I am very much involved in / with fashion clothing.	○	○	○	○	○	○	○

I would say that I am often preoccupied with fashion clothing.	○	○	○	○	○	○	○
I can really identify with fashion clothing.	○	○	○	○	○	○	○
I pay a lot of attention to fashion clothing.	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I consider fashion clothing to be a central part of my life.	○	○	○	○	○	○	○
I have a very strong commitment to fashion clothing that would be difficult to break.	○	○	○	○	○	○	○
I am very interested in fashion clothing.	○	○	○	○	○	○	○
Fashion clothing is an important part of my life.	○	○	○	○	○	○	○

→

This is the last page of the survey questionnaire.

What is your age?

What is your gender?

- Female
- Male
- Other; Prefer not to answer

Which of the following best describes your ethnicity/race?

- White / Caucasian
- Middle Eastern and North African
- Asian
- American Indian or Alaska native
- Native Hawaiian or other Pacific Islander
- Hispanic or Latino
- Black, African, African American
- Other

What is the highest degree or level of school you have completed?

If you are currently enrolled, choose the highest degree received.
When you are currently in college, choose 'Some college, but no degree'.

- No schooling completed
- Elementary school
- High school or equivalent (e.g., GED)
- Some college, but no degree
- Associate's degree
- Bachelor's degree
- Master's degree
- Professional degree
- Doctoral degree
- Other

What is your marital status?

- Divorced
- Single
- Separated

Married

Widowed

Other; Prefer not to answer

Which of the following best describes your annual income?

Less than $25,000

$25,000 - $49,999

$50,000 - $74,999

$75,000 - $99,999

$100,000 or more

Which of the following options would best describe your job situation?

Full-time

Retired

Part-time

Unemployed

Other; Prefer not to answer

Appendix C. Study 2 Post Hoc Pairwise Comparisons

Dependent Variable	(I) condition	(J) condition	Mean Difference (I-J)	SE	Sig.
Perceived Experience	AI	'Vella'	-0.13	0.14	.795
		Human-AI collaboration	-10.35	0.21	<.001
		Human	-50.23	0.11	<.001
	Humanized AI designer 'Vella'	AI	0.13	0.14	.795
		Human-AI collaboration	-10.22	0.22	<.001
		Human	-50.09	0.13	<.001
	Human-AI collaboration	AI	10.35	0.21	<.001
		'Vella'	10.22	0.22	<.001
		Human	-30.88	0.21	<.001
	Human	AI	50.23	0.11	<.001
		'Vella'	50.09	0.13	<.001
		Human-AI collaboration	30.88	0.21	<.001
Perceived Agency	AI	'Vella'	0.28	0.26	.707
		Human-AI collaboration	-0.36	0.25	.481
		Human	-30.00	0.19	<.001
	Humanized AI designer 'Vella'	AI	-0.28	0.26	.707
		Human-AI collaboration	-0.64	0.26	.075
		Human	-30.27	0.20	<.001
	Human-AI collaboration	AI	0.36	0.25	.481
		'Vella'	0.64	0.26	.075
		Human	-20.63	0.20	<.001
	Human	AI	30.00	0.19	<.001
		'Vella'	30.27	0.20	<.001
		Human-AI collaboration	20.63	0.20	<.001
Perceived Design Expertise	AI	'Vella'	0.03	0.20	1.00
		Human-AI collaboration	-0.11	0.20	1.00
		Human	-10.64	0.20	<.001
	Humanized AI designer 'Vella'	AI	-0.03	0.20	1.00
		Human-AI collaboration	-0.15	0.20	1.00
		Human	-10.67	0.20	<.001
	Human-AI collaboration	AI	0.11	0.20	1.00
		'Vella'	0.15	0.20	1.00
		Human	-10.53	0.20	<.001
	Human	AI	10.64	0.20	<.001
		'Vella'	10.67	0.20	<.001
		Human-AI collaboration	10.53	0.20	<.001
Product Attitude	AI	'Vella'	-0.15	0.24	1.00
		Human-AI collaboration	0.04	0.24	1.00
		Human	-0.72	0.24	.018
	Humanized AI designer 'Vella'	AI	0.15	0.24	1.00
		Human-AI collaboration	0.19	0.24	1.00
		Human	-0.58	0.24	.102
		AI	-0.04	0.24	1.00

	Human-AI collaboration	‘Vella’	-0.19	0.24	1.00
		Human	-0.76	0.24	.01
	Human	AI	0.72	0.24	.018
		‘Vella’	0.58	0.24	.102
		Human-AI collaboration	0.76	0.24	.01
Purchase Intention	AI	‘Vella’	-0.32	0.25	1.00
		Human-AI collaboration	-0.33	0.25	1.00
		Human	-0.64	0.25	.057
	Humanized AI designer ‘Vella’	AI	0.32	0.25	1.00
		Human-AI collaboration	0.00	0.25	1.00
		Human	-0.32	0.25	.78
	Human-AI collaboration	AI	0.33	0.25	1.00
		‘Vella’	0.00	0.25	1.00
		Human	-0.32	0.25	1.00
	Human	AI	0.64	0.25	.057
		‘Vella’	0.32	0.25	.78
		Human-AI collaboration	0.32	0.25	1.00
Brand Attitude	AI	‘Vella’	-0.20	0.18	1.00
		Human-AI collaboration	-0.16	0.18	1.00
		Human	-0.50	0.18	.038
	Humanized AI designer ‘Vella’	AI	0.20	0.18	1.00
		Human-AI collaboration	0.05	0.18	1.00
		Human	-0.29	0.18	.618
	Human-AI collaboration	AI	0.16	0.18	1.00
		‘Vella’	-0.05	0.18	1.00
		Human	-0.34	0.18	.358
	Human	AI	0.50	0.18	.038
		‘Vella’	0.29	0.18	.618
		Human-AI collaboration	0.34	0.18	.358