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Investigating the Influence of AI Tools Versus Human Agents on Consumer Experience in Skincare Diagnosis and Product Recommendations

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Résumé

Les détaillants en soins de la peau adoptent de plus en plus de nouveaux assistants d'achat virtuels, notamment des outils de diagnostic de peau alimentés par l'IA, afin d'améliorer l'expérience des consommateurs et leur offrir des recommandations de produits plus précises et personnalisées. Bien que ces innovations promettent des taux de conversion et d'achat plus élevés, les réactions des consommateurs face à ces nouveaux outils restent peu étudiées, contrairement à des systèmes de recommandations plus communs. Cette recherche examine l'influence des outils de diagnostic de peau par l'IA sur les intentions d'achat et la satisfaction liée à l'expérience d'achat, en les comparant aux questionnaires auto-administrés. Les résultats montrent que les outils de diagnostic de peau par l'IA réduisent les intentions d'achat des consommateurs et la satisfaction liée à l'expérience d'achat. Des analyses de médiation révèlent que ces effets négatifs sont dus à de faibles perceptions de contrôle et de personnalisation. Cette étude identifie une condition limite, démontrant que l'ajout d'une tâche de mesure (c'est-à-dire des questions contextuelles) peut atténuer ces effets en renforçant la personnalisation perçue. Cette recherche contribue à la littérature sur la personnalisation assistée par l'IA en distinguant les outils de diagnostic de peau par l'IA des systèmes de recommandation conventionnels (ici, les questionnaires auto-administrés) et en explorant les facteurs influençant l'acceptation de l'IA. D'un point de vue managérial, ces résultats offrent des pistes concrètes pour les marques de beauté et de soins souhaitant intégrer des outils alimentés par l'IA.

Mots clés : intelligence artificielle, outils de diagnostic de peau, expérience du consommateur, perception de contrôle, perception de personnalisation, intentions d'achat, systèmes de recommandation, satisfaction avec l'expérience d'achat

Méthodes de recherche : Cette recherche se compose de trois études expérimentales en ligne comparant les réactions des consommateurs à des recommandations de produits basées sur des outils de diagnostic de peau fourni par l'IA versus un questionnaire auto-administré. Des analyses de médiation et de médiation modérée ont été menées afin d'examiner les rôles de la perception de contrôle et de la perception de personnalisation, et de tester une condition limite.

Abstract

Skincare retailers are increasingly adopting novel digital shopping assistants, particularly AI diagnostic tools, to enhance online consumers' experience by offering more precise and personalized product recommendations. While these innovations promise greater conversion rates and increased purchasing behavior, there is still limited understanding of how consumers respond to them compared to more common recommendation systems. This research investigates the impact of AI diagnostic tools on purchase intentions and satisfaction with the shopping experience by comparing them to self-reported questionnaires. The findings consistently show that AI diagnostic tools reduce both purchase intentions and satisfaction with the shopping experience. Mediation analyses reveal that these negative effects are driven by lower perceived control and perceived personalization. Furthermore, this study identifies a boundary condition, demonstrating that the inclusion of a measurement task (i.e., contextual questions) can mitigate these effects by enhancing perceived personalization. This research contributes to the literature on AI recommendations by distinguishing novel AI diagnostic tools from conventional recommender systems (i.e., self-reported questionnaire in this research) and by exploring factors contributing to consumers' acceptance of AI. From a managerial perspective, the findings offer actionable insights for skincare retailers seeking to implement AI tools.

Keywords: artificial intelligence, consumer experience, AI diagnostic tools, digital shopping assistant, perceived control, perceived personalization, purchase intentions, recommendation systems, satisfaction with shopping experience

Research methods: The research consists of three online experimental studies that compare consumer responses to product recommendations based on AI diagnostic tools versus self-reported questionnaires. Mediation and moderated mediation analyses were conducted to examine the roles of perceived control, perceived personalization, and to test a boundary condition.

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List of Abbreviations

AI: Artificial Intelligence

RA: Recommendation Agent

RS: Recommendation Systems

Preface

Finding a suitable thesis topic was not an easy task for me. I spent a long time exploring different directions without being able to commit to a specific idea. As I am passionate about beauty and skincare, and currently work in the cosmetics industry, I wanted to choose a topic that would align with this field. It was also important to me that this research project resonates, in some way, with my professional experience. My goal was not purely academic; I also hoped that this thesis would offer insights that could be useful in my work, even in a general or reflective sense.

The turning point came during a presentation at my workplace, delivered by a consulting firm specializing in market research. They introduced us to key upcoming trends in the cosmetics industry, one of which was the growing demand for personalized customer experience. It was during that presentation that I first heard about AI diagnostic tools, such as Haut.AI. This innovation immediately sparked my curiosity and raised several questions, both about the technology itself and the consumer experience it aims to enhance.

This is how the idea for this thesis emerged: at the intersection of personal interest, professional context, and curiosity about emerging technologies in the beauty industry.

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From the very beginning, even before I had chosen a clear topic, he was incredibly patient, supportive, and reassuring. His thoughtful advice and calm presence helped me navigate the many doubts I had in the early stages of this work. He was consistently available, understanding, and attentive to my needs, especially considering that I was working alongside this research.

His support and dedication played a key role in the development of this thesis. I am truly grateful for his encouragement and for the respectful, flexible supervision he offered throughout the process.

Chapter 1: Introduction

The global revenue in the skincare segment of the beauty and personal care market is estimated at 190.3 billion USD in 2024, with an expected growth of 37.6 billion USD (+18.96%) between 2025 and 2030 (Statista, 2024). The United States leads the skincare market segment by generating approximately 24.9 billion USD in revenue in 2024 (Statista, 2024). Within this segment, facial skincare represents the largest subsegment in the U.S., contributing to 15.6 billion USD in 2024, with an expected increase of 3.5 billion USD (+21.69%) by 2030 (Statista, 2024). According to a survey conducted in the United States 2023, most respondents who recently purchased skincare products did so in-store, while 38% of respondents opted for online channels (Statista, 2024). In 2023, skincare is the most popular segment in the cosmetic industry, representing 40% of the market share (Statista, 2024). These figures highlight the skincare industry's continued dominance and growth potential, making it a key contextual industry for both brands and researchers.

Consumers are gaining awareness about skincare ingredients and their effects within this segment. Thus, there is a higher demand for products featuring specific ingredients, such as antioxidants, hyaluronic acid, and retinol, tailored to their specific needs (Fortune Business Insights, 2025). This growing consumer awareness has resulted in significant investments in research and development, driving the expansion of the skincare market through the continuous introduction of innovative skincare products designed to meet any of those specific concerns. In 2024, more than 25% of all new brands came from the beauty and personal care industry (Euromonitor International, 2024). However, the constant innovations and abundance of product choices are increasing the complexity of the consumer's decision-making process, making it more challenging to identify the most fitting products to integrate into their daily skincare routine. In response to this increasing complexity, companies are developing digital shopping assistants to help consumers simplify the decision-making process, such as quizzes, self-reported questionnaires, and, more recently, AI diagnostic tools that support consumers in navigating product choices and finding the most tailored solutions to their needs.

Hyper-personalization has emerged as a dominant trend in 2024 and is likely to continue in 2025, with a forecast impact on online sales of 21.3% for online cosmetics and beauty retailers in the U.S. (Clark, 2025). As the demand for hyper-personalization continues to rise, leading beauty companies and retailers, such as L'Oréal, Sephora, or Ulta, are turning to artificial intelligence (AI) to enhance the accuracy of product recommendations (Clark, 2025). In 2024, over 70% of U.S. digital retailers have recognized the potential impact of AI personalization in 2024 (Perkins, 2024). Moreover, 64% believe personalized experiences, such as AI, AR, and VR apps, will be highly influential by 2027 (Euromonitor International, 2023). The skincare industry was one of the first to adopt artificial intelligence (AI) and augmented reality (AR) solutions as a way to improve consumer skincare journey (Chang, 2023). Emerging interactive AI diagnostic tools like EveLab Insight enable consumers to better understand their skin health through virtual skin diagnosis technology, marketed as easy, fast, and precise skin consultations (BeautyMatter Studio, 2025). Thus, skincare industry companies are leveraging AI for personalized product suggestions, such as pioneering AI diagnostic tools. Platforms such as EveLab Insight integrate advancements in medical imaging research, machine learning, artificial intelligence, and skin-related technology to enable consumers to gain deeper insight into their skin health (BeautyMatter Studio, 2025). These AI diagnostic tools give precise virtual skin assessments that help skincare providers offer highly tailored product recommendations that match their consumers' needs. By improving diagnostic accuracy, these technologies enhance the shopping experience and increase consumers' trust, leading to higher engagement (Chang, 2023). According to Haut.AI, a leading AI company in the skincare industry, brands implementing AI skin analysis tools observe an average increase of 62% in customer conversion rates, alongside a 34% rise in shopping cart value (Haut.AI, n.d.).

Despite these promising claims, existing literature on AI recommendation systems highlights notable limitations, mainly regarding their lack of empathy and human-centered aspects compared to traditional agents (e.g., skincare experts, in-store consultants, etc.). These limitations affect consumer adoption and satisfaction with AI tools. Additionally, while current research has focused mainly on AI product recommendations, limited attention has been given to the impact of novel diagnostic technologies powered by AI. AI diagnostic tools represent a distinct and emerging form of recommendation technology. Unlike conventional AI recommendation systems that rely on explicit consumer input, such as self-reported questionnaires where consumers manually describe their skincare concerns, preferences, or routines, AI diagnostic tools often operate by analyzing images of the consumer's face or other biometric data. For example, Haut.AI, reports using algorithms trained on more than 3 million facial images to evaluate over 150 unique facial biomarkers and assess more than 15 core skin health metrics. These tools employ computer vision and machine learning techniques to detect skin conditions such as acne, redness, dryness, or wrinkles and generate tailored product recommendations based on automated analysis. Their primary goal is to simplify the recommendation process by reducing the cognitive burden on consumers, making it faster and more personalized. In doing so, AI diagnostic tools aim to replace or enhance more common and human-centered recommendation systems, such as self-reported questionnaires, which rely heavily on consumers' ability to accurately self-assess and articulate their needs. The skincare industry is at the forefront of this technological shift. However, little is known about how consumers react to those different sources of information, whether the AI generates insights directly from images or relies on consumer-provided data. Understanding this distinction is crucial to evaluating how AI influences consumer trust and decision-making in skincare purchases.

To better understand how consumers respond to emerging AI technologies in the skincare domain, this research investigates the effectiveness of AI diagnostic tools compared to a more common recommendation system. Specifically, we compare consumers' purchase intentions and satisfaction with the shopping experience when using an AI diagnostic tool versus a self-reported questionnaire. Across three experimental studies, we show that consumers report lower satisfaction and purchase intentions when interacting with an AI diagnostic tool compared to a self-reported questionnaire. We further demonstrate that these negative effects are mediated by perceived control and perceived personalization, with perceived personalization consistently emerging as the stronger driver. Finally, we identify a boundary condition: introducing a measurement task (i.e., a brief set of contextual questions) increases the perceived personalization in the AI tool condition and eliminates the negative effect. This research contributes to the literature by examining consumer reactions to AI in a novel context: diagnostic technologies, demonstrating a consistent negative effect on consumer outcomes. It also examines the role of two psychological mechanisms underlying these reactions, such as perceived control and perceived personalization, and highlights the dominance of the latter. In addition, it extends prior work by showing that measurement tasks can function as effective design interventions, helping to mitigate resistance toward autonomous AI tools. From a managerial perspective, these findings highlight the importance of careful implementation when integrating AI diagnostic tools into customer journey. Because these tools can lead to negative consumer responses, managers must consider how much control and personalization the consumer perceives when designing the tool. Our findings show that design elements such as measurement tasks play a key role in shaping personalization perceptions; thus, removing them may inadvertently reduce the tool's effectiveness.

The rest of this thesis is organized as follows: the next chapter reviews relevant literature on the skincare context and AI in consumer decision-making, followed by the development of hypotheses. The following chapter presents our experimental studies, including methodology and presentation of the results. The final chapter discusses the theoretical and practical implications of our findings.

Chapter 2: Literature Review

This literature review is divided into two sections. The first explores the growing impact of the skincare industry and its emotional significance for consumers, emphasizing the high-risk nature of skincare purchases. The second section focuses on the emergence of artificial intelligence (AI) in marketing, with particular attention to AI recommendation systems. It discusses factors driving its adoption, it examines the conditions under which AI is preferred over human agents, and it identifies key factors of its effectiveness, such as perceived control and perceived personalization.

Emotional Significance and Risk Perception of Skincare

The skincare industry (Statista, 2024) is the largest sub-segment of the beauty and personal care market in the United States and holds deep psychological and social significance for consumers, particularly women. While skincare is often framed as a matter of hygiene or aesthetics, it plays a critical role in shaping self-construction, self-worth, identity, and social perception (Baudson et al., 2016; Harter & Leahy, 2001). Prior research has shown that appearance-related concerns are among the strongest predictors of self-esteem, especially during adolescence, a period marked by declining satisfaction with appearance among girls (Baudson et al., 2016; Harter & Leahy, 2001). Women tend to experience greater body dissatisfaction than men across all age groups (Esnaola et al., 2010), as their skin is particularly sensitive to age-related changes, which often leads to more critical self-assessments (Samson et al., 2010). These findings suggest a greater internalization of beauty standards and increased vulnerability to self-image concerns among women. Because skin changes are both visible and symbolically associated with attractiveness and youth (Samson et al., 2010), they can significantly impact emotional well-being and social behavior (Dreno & Layton, 2021; Samson et al., 2010). For instance, research links skin-related concerns such as wrinkles, pigmentation, and acne to lower self-confidence, anxiety, depression, and even social withdrawal (Dreno & Layton, 2021; Özkesici Kurt, 2022; Tanghetti et al., 2014). This relationship is further underlined by the concept of “unsuccessful aging”, or aging-anxiety, in which declining appearance correlates with diminished self-care and psychological distress (Barrett & Robbins, 2008;

Koblenzer, 1996; Pleyers & Vermeulen, 2021). As a result, skincare becomes not only a cosmetic concern but a perceived necessity. These emotional and psychological pressures significantly influence consumption patterns. Studies show that physical attractiveness and aging concerns affect purchase intentions (Pleyers & Vermeulen, 2021; Samir et al., 2022), and that low self-concept is associated with higher skincare consumption behavior (Ulayya & Andriani, 2023). Moreover, social media and influencer culture reinforce unrealistic expectations, particularly among young women who are driven to pursue idealized, acne-free skin (Ulayya & Andriani, 2023; Putri, 2024). Furthermore, they proved those social media influencers and algorithms tend to distort perceptions between necessary and desired products, influencing skincare consumption (Putri, 2024). Overall, these findings underline the importance of skincare not just as a cosmetic concern, but as a deeply personal and emotionally significant aspect of consumers' lives, closely tied to self-image, well-being, and identity.

A specificity of the skincare industry is that, although products can be tested, they typically require prolonged use before visible results appear, making the purchase decision inherently high-risk for consumers (Rodgers, 2023). This forces consumers into a trial-and-error process, which can be stressful and costly. A study found that 87% of women feel concerned when trying new skincare items, worrying that new products might not work, cause irritation, or even worsen their skin (Rodgers, 2023). Since they often have to buy and use the product over time to see results, this also creates a financial risk, especially if multiple products must be tested before finding the right one. The same study reported that 90% of women experience some level of frustration with finding skincare products that actually work (Rodgers, 2023). This frustration is amplified by the inherent complexity of the skincare category, which includes a wide variety of products, ingredients, formulations, and attributes that consumers must evaluate. Research shows that a large number of product attributes significantly increase information overload, ultimately making consumers feel less satisfied, less confident, and more confused (Lee & Lee, 2004). Given the emotional weight of skincare, establishing a consistent and effective routine seems crucial. Indeed, the usage of cosmetic products, including make-up, fragrances, and skincare, has been shown to positively impact the quality of life, well-being, self-esteem, social relationships, and even biological stress markers in women, both in everyday life and clinical contexts (Battie & Verschoore, 2011). Similarly, Zhang et al. (2020) found that regular skincare regimens improve empowerment, happiness, and self-esteem, highlighting that an effective skincare routine enhances overall well-being. However, to ensure proper effectiveness, research increasingly emphasizes the importance of individualized and patient-centered approaches when addressing skin imperfections, particularly given the unique concerns and conditions that vary from person to person (Dreno & Layton, 2021). For instance, skincare motivations evolve with age: women under 60 often seek anti-aging products to maintain attractiveness and manage social pressures, whereas women over 60 are more likely to pursue skincare for emotional well-being (Pleyers & Vermeulen, 2021). Thus, personalization helps reduce the cognitive effort of choosing products by filtering out irrelevant options and offering recommendations that match consumers' needs, ultimately leading to higher satisfaction (Liang et al., 2006).

Emergence of New Technologies in Skincare

Given the size of the skincare market and the strong emotional and psychological impact that skincare decisions have on consumers, skincare products can be considered high-risk purchases. Their personal, visible, and long-term nature makes the purchase decision process complex and anxiety-inducing for many consumers. As such, retailers are under pressure to develop innovative shopping assistants that simplify decision-making and support consumers in choosing the right products. Many skincare retailers have implemented self-reported questionnaires to address this need for personalization, a commonly used digital shopping assistant in online skincare purchases. Self-reported questionnaires ask consumers to share information about their skin type, concerns, and preferences, which allows the system to tailor product recommendations accordingly. This series of explicit questions can be considered a measurement task, defined by Kramer (2007) as a process in which users actively provide input about their preferences, needs, or context. This measurement task process plays a key role in the effectiveness of self-reported questionnaire tools, as it provides relevant data for the system and encourages users to participate actively in the recommendation process, helping them better understand their needs as they complete the task (Kramer, 2007). Yet, emerging technologies like AI diagnostics tools are progressively replacing those more conventional recommendation systems, particularly on retail websites who seek to modernize the consumer experience by offering faster, data-driven, and potentially more personalized recommendations (BeautyMatter Studio, 2025). These tools analyze facial images to detect visible skin conditions (e.g., wrinkles, acne, pigmentation) and generate product recommendations based on biometric insights (BeautyMatter Studio, 2025; Haut.AI, n.d.). Compared to self-reported questionnaires, AI diagnostic tools require minimal input from the consumer, often positioning them as more objective and precise. As such, they aim to help consumers navigate skincare decisions more confidently by reducing uncertainty and offering tailored insight-driven product suggestions. However, despite their growing prevalence, little research has been conducted on these novel AI diagnostic tools. As a result, there is limited understanding of how consumers perceive and respond to these tools, especially compared to more common recommendation systems. While these AI diagnostic tools promise greater precision and higher conversion rates (Haut.AI, n.d.), prior research in consumer contexts has shown less favorable outcomes and potential resistance to AI. The next section of this literature review explores the emergence of artificial intelligence (AI) in marketing, with particular attention to AI recommendation systems.

Contextualization of AI in Marketing

Integrating artificial intelligence (AI) into marketing has transformed how firms engage with consumers, enabling real-time, data-driven personalization across the customer journey. Häubl & Trifts (2000) are among the earliest researchers empirically demonstrating the importance of interactive decision aids (IDAs) in online consumer decision-making. They define interactive decision aids, also called recommendation systems (RSs), as decision support tools that interactively assist consumers in evaluating alternatives by reducing information overload and increasing decision quality (Häubl & Trifts, 2000). Within this framework, they differentiate two main tools: recommendation agents (RAs), which filter product options based on consumer preferences to provide tailored alternatives, and comparison matrices, which allow consumers to compare product attributes side by side (Häubl & Trifts, 2000). These tools simplify product selection and boost decision confidence (Häubl & Trifts, 2000). Recommendation systems are digital tools that generate personalized product or content suggestions by analyzing user behavior, preferences, and data from similar users. Within this domain, recommendation agents (Ras) refer as specific types of user-facing interfaces (e.g., chatbot, digital expert) (Häubl & Trifts, 2000; Xiao & Benbasat, 2007), but are often interchanged with RSs among prior research. Traditionally, RSs use collaborative filtering and/or content-based filtering methods to anticipate preferences (Ansari et al., 2000; O'Donovan & Smyth, 2005). Collaborative filtering relies on similar users' preferences, while content-based filtering matches products attributes to a user's past choices. Ansari et al. (2000) also proposed a Bayesian preference model incorporating five factors: a user's past choices, preferences for attributes, other users' choices, expert opinions, and demographics, to increase prediction accuracy.

When designed around the consumer experience, recommendation agents, and more generally RSs, reduce cognitive effort and build trust (Knijnenburg et al., 2012; Xiao & Benbasat, 2007). Recommendation systems can be salesperson-oriented or evolve into customer-facing tools such as the ones used by skincare retailers—for example, Haut.AI—designed to replace the salesperson entirely (Ahearne & Rapp, 2010), thus entirely based on artificial intelligence. Artificial Intelligence (AI) has been defined as a system capable of learning from external data to achieve goal-directed tasks (Haenlein & Kaplan, 2019). Among the different types of AI, Huang and Rust (2021) classify AI RSs as "thinking AI," a system that recognizes data patterns and supports decision-making, such as digital shopping assistants, in contrast with "mechanical AI," which is designed for automating repetitive and routine tasks, or "feeling AI" which engages in emotional analysis and human interaction (e.g., social robots). According to this classification, AI diagnostic tools in skincare fall under the "thinking AI" category, as they analyze biometric data (e.g., facial images) to identify skin conditions and generate personalized product recommendations based on algorithmic reasoning. Their core function is to enhance decision-making by offering data-driven insights rather than emotional engagement or task automation.

AI recommendation systems influence more than purchase decisions; they mediate the entire shopping experience (Foroudi et al., 2018), delivering hyper-personalized content across channels (Haleem et al., 2022) and marketing practices, such as customer relationship management, segmentation, pricing, and content strategy (Chintalapati & Pandey, 2022; Hicham et al., 2023; Vlačić et al., 2021). These technologies generate consumer data, which enables more effective methods, generates more profound insights, and drives better decisions, thereby creating a "flywheel" of continuous improvement in marketing practices (Hoffman et al., 2022). However, their rise raises ethical concerns around autonomy, bias, and overreliance (Guha et al., 2021; Puntoni et al., 2021).

Drivers and Barriers to AI Adoption: the Role of Trust

Consumer adoption of AI tools is influenced by a combination of emotional, cognitive, and contextual factors. On the driver side, emotional and experiential factors are key to AI acceptance. Ebrahimi et al. (2022) found that affective reactions, such as enjoyment, confidence, and perceived control, play a more influential role in consumer adoption of AI recommendation systems than purely utilitarian benefits. Similarly, Inman and Nikolova (2017) demonstrate that tools that enhance convenience and perceived personalization generate stronger consumer responses, including patronage and positive word-of-mouth. Additionally, Foroudi et al. (2018) also found that social influence, in the form of peer reviews, testimonials, and shared experiences, can significantly strengthen perceived value and foster trust, thus promoting adoption. However, consumers also face several psychological and ethical barriers to adopting AI technologies. Riegger et al. (2021) identify common concerns including discomfort with human-centered technologies (the "uncanny valley"), fear of manipulation, loss of autonomy, and privacy concerns. In their research, Riegger et al. (2021) outline five key paradoxes that consumers confront: exploration vs. limitation, staff presence vs. absence, humanization vs. dehumanization, personalization vs. privacy, and personal vs. retailer-controlled devices. These paradoxes demonstrate the tension between consumer expectations and technological capabilities. However, trust emerges as a key factor in reducing these barriers and as a foundation for consumer acceptance and long-term adoption.

Among these drivers and barriers, trust has emerged as a central theme in research on AI technologies and has been found to be a pivotal factor in shaping consumer adoption. Ameen et al. (2021) found that trust and perceived sacrifice shape how consumers evaluate AI personalization and service quality. Researchers distinguish trust in AI technologies into two categories: cognitive trust and affective trust. On the cognitive side, explainability affects trust, as transparency increases the understandability and justifiability of algorithmic decisions (Adadi & Berrada, 2018; Kizilcec, 2016), particularly in utilitarian contexts (Ameen et al., 2021; Buçinca et al.,; 2021Chen et al., 2024). Moreover, Shin (2020) emphasizes FATE principles (fairness, accountability, transparency, and explainability) as foundational to building trust. Ebrahimi et al. (2022) further emphasize that perceived personalization and intuitive interfaces can enhance trust in interactive AI settings. Further research argue that trust in AI is often more context-dependent and fragile than trust in human agents, requiring alignment between system capabilities and consumer expectations (Glikson & Woolley, 2020). On the other hand, Mahmud et al. (2022) stress that trust is shaped by emotional and contextual factors such as autonomy, fairness, and transparency. Kaplan et al. (2023) reinforce this by showing that while performance-based attributes (e.g., reliability, predictability) are strong trust drivers, non-performance factors (e.g., personality, anthropomorphism, communication style) also play a significant role, especially when contextual risk is high. Finally, Schepman and Rodway (2023) validated the GAAIS scale, which links general attitudes toward AI to Big Five personality traits, showing that openness to experience and interpersonal trust predict more favorable attitudes toward AI technologies. Together, these insights underscore that consumer adoption of AI recommendation systems depends not only on performance and personalization but also on emotional responses, perceived fairness, and trust-building mechanisms. Building on the importance of trust, an emerging question is when and under which conditions consumers are more likely to trust or prefer AI tools over human agents.

When Do Consumers Prefer AI Over Humans?

Although AI tools offer clear efficiency, accuracy, and scalability benefits, research shows that consumers do not always welcome them. AI performs better than humans in analytical or mechanical tasks—such as forecasting or generating product matches (Chang, 2022; Logg et al., 2019). However, consumers often reject AI in tasks that involve subjectivity, emotional intelligence, or autonomous decision-making. This distinction is known as the “word-of-machine” effect, meaning consumers favor AI in functional contexts but resist it in emotional or sensory ones (Longoni & Cian, 2022). For example, Huang & Wang (2023) found that AI recommendation systems seem less persuasive than humans, especially in sensitive settings like medicine. Similarly, Castelo et al. (2019) highlight that consumers trust AI more for objective tasks but are hesitant when tasks feel personal or emotional. Consumers often feel that AI lacks empathy, leading to impersonal or cold interactions (Barari et al., 2024; Liu-Thompkins et al., 2022). This tendency to lose confidence in AI more quickly than in humans, especially after mistakes, is known as algorithm aversion (Dietvorst et al., 2015; Jussupow et al., 2020; Wien & Peluso, 2021). Even when AI performs better, consumers may prefer human recommendations, particularly for high-stakes or emotional decisions, like choosing the proper skincare regimen. This effect often fades as consumer expertise increases or, once again, when the task feels more personal (Logg et al., 2019). Consumer preferences also vary depending on the type of product: human recommenders tend to be more persuasive for hedonic products, as they help consumers connect the product to their emotions and desires, whereas AI recommendation systems are generally preferred in utilitarian contexts (Longoni & Cian, 2022; Wien & Peluso, 2021). Finally, researchers found that a last model could be used: a hybrid model that combines AI efficiency with human oversight to increase acceptance (Barari et al., 2024; Jussupow et al., 2020). Framing AI as an advisory tool rather than a fully autonomous agent can reduce perceptions of dehumanization while reassuring consumers that human expertise remains involved (Barari et al., 2024; Jussupow et al., 2020). Beyond the question of preference between AI and human agents, another critical factor influencing consumer experience with AI tools is the extent to which users feel involved and in control during the decision-making process. The following section explores how perceived control and user involvement shape consumer responses to AI recommendation systems.

Perceived Control and User Involvement

As AI tools become increasingly involved in consumers' purchase decision process, one key challenge is maintaining perceived control and autonomy (Ameen et al., 2021; André et al., 2018). While automation can improve convenience and accuracy, it may also reduce users' perceived involvement in the decision-making process, leading to increased resistance (André et al., 2018). This is particularly important because when consumers actively participate in the recommendation process, they report higher levels of trust, satisfaction, and purchase intention (Dabholkar & Sheng, 2012; Franke et al., 2009). These effects are particularly strong when recommendation agents (RAs) operate in two-way dialogues, allowing users to express preferences clearly and meaningfully. Kramer (2007) further emphasizes the importance of task transparency in these interactions; users are more likely to accept personalized offers when they recognize their explicitly stated preferences in the outcomes, especially if they are novices. Providing even minimal control over AI recommendation systems can significantly improve consumer experience. In their work on algorithm aversion, Dietvorst et al. (2018) found that consumers were more willing to adopt and trust an imperfect algorithm if they were allowed to modify its output even slightly. This small perception of control increased trust and satisfaction and improved consumers' perception of the algorithm's performance. These studies highlight that perceived control and active involvement are critical for building trust, improving consumer satisfaction, and ensuring sustainable AI adoption. Beyond perceived involvement, another crucial factor shaping consumer responses to AI recommendation systems is the extent to which the recommendations feel personally tailored and whether the system acknowledges the uniqueness of the individual's needs. This second dimension is the focus of the following section.

AI Personalization & Uniqueness Neglect

Personalization is key to building trust and enhancing consumer satisfaction in AI recommendation systems. According to Komiak and Benbasat (2006), when users perceive a system as personalized, it strengthens both cognitive trust (belief in the system's competence) and emotional trust (a feeling of safety and comfort). A significant determinant of AI personalization effectiveness is the distinction between actual and perceived personalization, the latest being how personalized the experience feels to the consumer (Li, 2016). Li's (2016) research highlights that perceived personalization often better addresses consumers' need for personalization than actual personalization, highlighting the importance of consumer experience over technical accuracy. This gap is closely tied to the concept of uniqueness neglect, where consumers believe that AI fails to account for their individual context, leading to feelings of being misunderstood or generalized (Barari et al., 2024). Similarly, Longoni et al. (2019) showed that consumers often resist AI in personal or emotionally charged domains, such as healthcare, due to skepticism about AI's ability to understand their uniqueness despite superior accuracy compared to human agents. Their findings suggest that framing AI as personalized or integrating human oversight can mitigate this resistance. Another important factor is how preference input is managed. The method of eliciting preferences significantly shapes perceived personalization: explicit input (e.g., direct questions) enhances perceived accuracy and engagement but demands greater effort, while implicit input may feel seamless but risks lowering perceived involvement and personalization (Lavie et al., 2010; Li & Karahanna, 2015). Similarly, Franke et al. (2009) found that customization based on self-expressed preferences leads to higher purchase intentions, willingness to pay, and more positive attitudes, particularly when consumers clearly understand their preferences and are highly involved with the product category. Finally, recent research emphasizes that perceived personalization is heavily influenced by the system's interface design, communication style, and interaction flow (Adadi & Berrada, 2018; Hassija et al., 2024). Various design strategies, such as providing clear explanations, ensuring transparency, and fostering user-friendly interactions, are critical moderators of perceived personalization (Adadi & Berrada, 2018; Hassija et al., 2024). Personalization is an experiential phenomenon dependent on consumers feeling seen, heard, and involved throughout the process (Li & Karahanna, 2015; Verma et al., 2021). Without this emotional engagement, even the most accurate AI recommendations risk being perceived as generic or irrelevant.

This literature review highlights the growing relevance of AI in skincare consumer decision-making process. The skincare industry holds significant emotional importance, as skincare choices are closely tied to self-esteem, identity, and overall well-being. This emotional weight, combined with delayed outcomes assessments, makes skincare a high-risk purchase decision, where consumers face uncertainty and seek reassurance. To address these challenges, retailers have introduced new digital shopping assistants, among which AI diagnostic tools emerge as an innovative solution promising more accuracy and convenience than conventional self-assessment questionnaires. However, despite the rapid integration of AI into marketing, research indicates mitigated reactions to these AI tools, even though they are objectively more accurate. Factors influencing AI adoption include technological performance as well as consumer trust, emotional engagement, and perceived relevance. Consumer preference between AI tools or human agents depends on context, product type, and the ability of the system to provide emotional resonance and personalization. Across these dynamics, two psychological mechanisms, perceived control and perceived personalization, consistently emerged as key factors shaping consumer trust, satisfaction, and behavioral intentions when interacting with AI tools. Overall, the literature suggests that the success of AI diagnostic tools in emotionally charged and high-risk contexts like skincare depends less on technological accuracy alone and more on a thoughtful, user-centered design that includes perceived control and perceived personalization. The following section introduces our research hypotheses, developed to explore how these mechanisms influence consumer responses to AI diagnostic tools compared to more common recommendation systems (i.e., self-reported questionnaire). Drawing from the insights discussed in this literature review, the following section presents our research hypotheses on how perceived control and perceived personalization influence consumer responses to AI diagnostic tools.

Chapter 3: Hypothesis Formulation

This research intends to investigate how AI diagnostic tools, compared to self-reported questionnaires, influence consumer outcomes in terms of purchase intentions and satisfaction with the shopping experience in the skincare product category. Specifically, the digital shopping assistants compared in this research (i.e., the AI diagnostic tool and self-reported questionnaire) serve the same purpose of understanding consumers' skin conditions, needs and preferences to tailor product recommendations accordingly. However, they differ in their design and consumer experience. The AI diagnostic tool aims to understand consumers' current skin conditions and needs based mainly on the analysis of a selfie image uploaded by the consumer. The AI diagnostic tool uses the selfie uploaded by the consumer to prepare a skin report, which rates the consumer's skin condition on several metrics. The product recommendations are then developed based on this skin report (e.g., to improve lower ratings and maintain higher ratings). In contrast, the self-reported questionnaire asks consumers to respond directly to a series of questions about their skin condition (e.g., concerns, problems, etc.), needs, and preferences. In this case, the product recommendations depend on the information the consumer provides in their answers to the questions. Although these digital shopping assistants have a similar purpose, AI diagnostic tools are becoming more common in the skincare industry because they are assumed to be superior to more conventional tools serving a similar purpose. However, past research on consumer reactions to AI hints toward the possibility of consumers not appreciating such AI tools as much as the intuition suggests despite them being objectively superior to more conventional tools. Next, drawing from past research on consumer reactions to AI tools, we develop our predictions about consumer reactions to using the AI diagnostic tool compared to the self-reported questionnaire.

Prior research has identified two critical psychological factors shaping consumer reactions to AI: perceived control and perceived personalization. Perceived control refers to how consumers feel they influence the decision-making process (André et al., 2018; Dietvorst et al., 2018). Perceived personalization reflects the extent to which consumers believe the recommendation is tailored to their individual needs and preferences (Komiak &

Benbasat, 2006; Li, 2016). Both factors have been shown to enhance consumer trust, satisfaction, and engagement with AI recommendation systems. Therefore, we suggest that these two constructs will drive the effectiveness of the digital shopping assistants examined in this research. More importantly, we argue that the nature of the AI diagnostic tool may lead to lower levels of perceived control and perceived personalization compared to the self-reported questionnaire. Unlike self-reported questionnaires, which actively involve consumers by requesting them to express their concerns and preferences, AI diagnostic tools typically operate passively, analyzing data such as images with minimal consumer input. Consumers do not participate in the process more than simply uploading a selfie without knowing how the AI diagnostic tools work. On the other hand, with self-reported questionnaires, consumers are more involved in the process and have a better understanding of how the tool works as it is very conventional. The lack of understanding of how the AI diagnostic tool works and lack of user involvement with it would thus lead to lower perceived control and perceived personalization compared to the self-reported questionnaire (Adadi & Berrada, 2018; Barari et al., 2024; Glikson & Woolley, 2020). In conclusion, we argue that the nature and design of the AI diagnostic tool would lead to lower perceptions of control due to a lack of consumers' understanding of how they work and consumer involvement in the process, compared to self-reported questionnaires.

Furthermore, we suggest that the AI diagnostic tool would lead to lower perceptions of personalization, drawing from past research demonstrating that consumers often resist fully autonomous systems because they feel that their uniqueness is not acknowledged or that they lack influence over the process (Franke et al., 2009; Longoni et al., 2019). This uniqueness neglect documented with AI tools leads to lower purchase intentions and reduced satisfaction (Dabholkar & Sheng, 2012; Franke et al., 2009). This is particularly important in the skincare domain, where emotional involvement and individual needs play a central role in purchase decisions. We suggest that the nature of the AI diagnostic tools, which is almost fully autonomous, will lead to perceptions of uniqueness neglect such that consumers would feel like their unique situation is not taken into consideration with the AI diagnostic tool compared to the self-reported questionnaire, resulting in lower levels of perceived personalization.

We argue that AI diagnostic tools would lead to lower levels of perceived control and perceived personalization due to their nature and design. Given that lower levels of perceived control and perceived personalization have been associated with poorer consumer outcomes, including reduced purchase intentions and lower satisfaction (Dabholkar & Sheng, 2012; Franke et al., 2009), we predict that the AI diagnostic tool will lead to less favorable outcomes than the self-reported questionnaire. Formally stated:

> **H_{1a}:** Consumers using an AI diagnostic tool (vs. self-reported questionnaire) will report lower purchase intentions.

> **H_{1b}:** Consumers using an AI diagnostic tool (vs. self-reported questionnaire) will report lower satisfaction with the shopping experience.

As previously discussed, the autonomous design of the AI diagnostic tool limits user involvement and understanding, thereby reducing perceived control and perceived personalization. Thus, we hypothesize that these two factors drive the effect of the digital shopping assistant on consumer outcomes. That is, the AI diagnostic tool leads to less favorable responses because it reduces perceived control and perceived personalization of the recommendation:

> **H_{2a}:** The negative effect of the AI diagnostic tool (vs. the self-reported questionnaire) on purchase intentions will be mediated by perceived control.

> **H_{2b}:** The negative effect of the AI diagnostic tool (vs. the self-reported questionnaire) on satisfaction with the shopping experience will be mediated by perceived control.

> **H_{3a}:** The negative effect of the AI diagnostic tool (vs. the self-reported questionnaire) on purchase intentions will be mediated by perceived personalization.

> **H_{3b}:** The negative effect of the AI diagnostic tool (vs. the self-reported questionnaire) on satisfaction with the shopping experience will be mediated by perceived personalization.

If, as hypothesized, perceived control and perceived personalization drive the negative effect of the AI diagnostic tool on purchase intentions and satisfaction with the shopping experience, then it follows that increasing either one of these factors should help mitigate the negative impact of the AI diagnostic tool. Said otherwise, our theorizing suggests that increasing perceived control or perceived personalization with the AI diagnostic tool should mitigate the negative effect we previously hypothesized.

In this research, we argue that adding a measurement task is one way of increasing perceived personalization by allowing consumers to share information. A measurement task is a process in which consumers are prompted to explicitly share their preferences, needs, and other significant information (Kramer, 2007). When consumers engage in such a task, they are more likely to perceive the resulting recommendations as personally relevant, particularly because they can recognize their own input in the outcome (Kramer, 2007). Indeed, past research suggests that hybrid recommendation systems that combine automated recommendations with consumer input are often better received than fully autonomous systems (Barari et al., 2024; Jussupow et al., 2020). These hybrid approaches improve perceived personalization by allowing consumers to share context, clarify concerns, or influence outcomes. Thus, by adding a measurement task, we intend to increase the perceived personalization of the consumer, one of the two factors influencing the outcomes. The measurement task in our research consists of a brief set of contextual questions (e.g., about stress, sleep, or environmental factors) designed to let consumers share information that may affect their skincare needs.

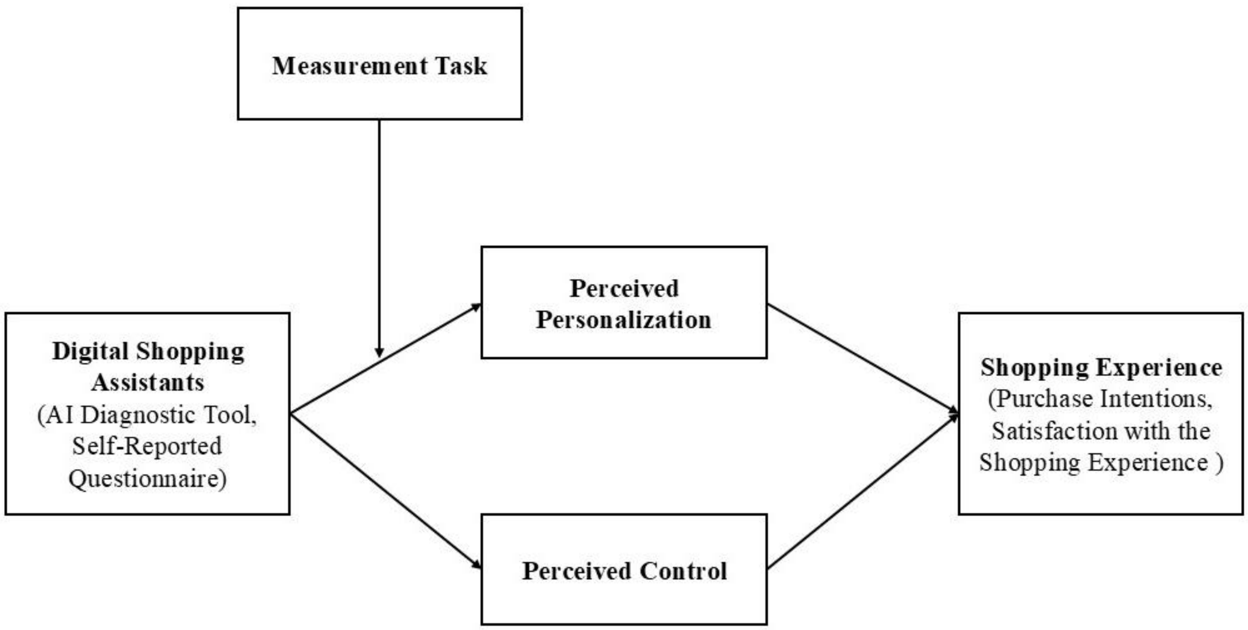
Specifically, we suggest that the measurement task should be effective in increasing perceived personalization with the AI diagnostic tools. The measurement task should introduce a moment for consumers to actively share input, which could restore perceived personalization by making the process more tailored and interactive. Therefore, we argue that including the measurement task in AI diagnostic tools would increase perceived personalization, increasing the effectiveness of this digital tool in terms of purchase intentions and satisfaction. However, for the self-reported questionnaire, we expect the measurement task to have little to no additional effect, as this tool already includes direct preference elicitation. In this case, adding a measurement task would only increase the number of questions, with marginal added benefits. Hence, we predict that when the measurement tool is present (i.e., added to the digital tool), purchase intentions and satisfaction in the AI diagnostic tool condition will increase due to increased perceived personalization, compared to when the measurement tool is absent (i.e., control conditions). However, we do not predict an effect of the measurement task in the self-reported questionnaire condition. Therefore, when the measurement task is present, we suggest an increase in the purchase intention and satisfaction in the AI diagnostic tool condition, while we do not predict a change in the self-reported questionnaire condition. As a result, we suggest that when the measurement task is present, the negative effect of AI diagnostic tool (vs. self-reported questionnaire) will disappear. In other words, we suggest that the predicted increase in purchase intentions and satisfaction the AI diagnostic tool condition when the measurement task is present would lead to a boundary condition. Formally stated:

> **H_{4a}:** When the measurement task is absent, consumers using an AI diagnostic tool (vs. self-reported questionnaire) will report lower purchase intentions, but this effect will disappear when the measurement task is present.

> **H_{4b}:** When the measurement task is absent, consumers using an AI diagnostic tool (vs. self-reported questionnaire) will report lower satisfaction with the shopping experience, but this effect will disappear when the measurement task is present.

The underlying hypotheses are visually represented in the conceptual model presented in Figure 1.

Figure 1 – Conceptual Model of the Effect of Digital Shopping Assistants on Shopping Experience



Chapter 4: Experiments

To test our hypothesis, we conducted three online experiments. First, Experiment 1 tested the main prediction that using an AI diagnostic tool (vs. a self-reported questionnaire) leads to lower purchase intentions and satisfaction with the shopping experience. Experiment 2 examined the role of perceived control and perceived personalization in the process underlying the effect of digital shopping assistant[1] on purchase intentions and satisfaction. Experiment 3 extends the previous experiments by demonstrating a managerially relevant boundary condition while testing our theorizing using a moderation approach. Since this thesis focuses on skincare products, an industry in which most consumers are women, we decided to set an inclusion across all experimental studies to recruit only participants who self-identify as female on the online platform we recruited them from. As a result, all participants in the following experiments identify as female.

Experiment 1

Experiment 1 explores whether the AI diagnostic tool, compared to a self-reported questionnaire, reduces purchase intentions and satisfaction with the shopping experience when purchasing skincare products online. In Experiment 1, participants were asked to imagine using either the AI diagnostic tool or the self-reported questionnaire as a shopping assistant while shopping for a new skincare routine. They indicated their purchase intentions for a new skincare routine and satisfaction with the shopping experience. Specifically, we manipulated shopping assistant such that half of the participants imagined using an AI diagnostic tool[2] while the other half imagined using a self-reported questionnaire while shopping online for a new skincare routine on a retailer's website.

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[1] From hereafter, "shopping assistant" will refer to digital shopping assistant, for the sake of brevity and to avoid repetition.
[2] From hereafter, "AI tool" will refer to AI diagnostic tool, for the sake of brevity and to avoid repetition.

Method

One hundred fifty-five participants who identify as female (M_{age} = 46.05, *SD* = 12.83) were recruited from Amazon Mechanical Turk (hereafter MTurk) to complete the single-factor between-participants experiment with two levels (shopping assistant: self-reported questionnaire, AI tool). At the beginning of the experiment, participants were asked to imagine shopping for a new skincare routine at the online store of a fictitious skincare retailer. They were told they had decided to use a shopping assistant available on the website. In the self-reported questionnaire condition, participants were presented with the shopping assistant named "Product Finder" and were provided with a brief explanation as to how the shopping assistant works. This scenario was designed to simulate the experience of using a self-reported tool for skincare recommendations. Participants were presented with a set of pre-answered questions about skin concerns and preferences and were asked to imagine that they themselves had completed the questionnaire and provided those answers. In the AI tool condition, participants were presented with the shopping assistant named "AI skin analysis," an AI diagnostic tool. They were told that the AI tool provides them with a skin report based on a selfie that they upload on the website. This scenario was designed to simulate the experience of using an AI diagnostic tool for skincare recommendations. The procedures described and the instructions provided in the scenario (i.e., the way participants were asked to imagine using the AI tool) closely mirrored commonly used procedures by similar real-world AI skincare tools. Accordingly, participants were presented with the instructions and were asked to imagine taking a selfie. Next, they imagined receiving a personalized skin report, which provided ratings from 0 to 100 on ten skin attributes: texture, wrinkles, firmness, blemish-prone, radiance, hydration, dark spot, oiliness/shine, dark circles, redness-prone. The experimental stimuli and questionnaires used in each experiment are available in Appendix A. After the shopping assistant manipulation (i.e., after imagining using one of the two shopping assistants), participants in both conditions were presented with a recommended skincare routine that consisted of three skincare products: a cleanser, a treatment, and a moisturizer. After reviewing a brief product description, participants indicated how likely they would be to purchase each product on two items (1 = not likely at all, 7 = very likely; 1 = not probable at all, 7 = very probable; $\alpha_{product\ 1}$ = .96, $\alpha_{product\ 2}$ =

.96, $\alpha_{product\ 3}$ = .98; adapted from Zúñiga, 2016). Next, participants reported their satisfaction with the shopping experience using three items ("*I would be satisfied with the shopping experience*," "*I would be happy with the shopping experience*," and "*I would be pleased with the shopping experience*"; 1 = strongly disagree, 7 = strongly agree; α = .97; adapted from Wang et al., 2018). The complete wording of all measurement scales and items used across all experiments is provided in Appendix B. Next, the participants responded to a three-item scale measuring the perceived realism of the shopping scenario to ensure that the scenarios included in the experiment were perceived realistic and the two experimental conditions did not vary in perceived realism (1 = strongly disagree, 7 = strongly agree; α = .91; adapted from Emrich et al., 2015). Finally, the participants answered a series of demographic questions before the study ended.

Results

We removed six participants who did not complete the experiment from the data, leaving a sample of 149 participants (M_{age} = 46.17, *SD* = 12.82).

Realism of the Shopping Scenario. A single-factor ANOVA with shopping assistant (self-reported questionnaire = –1, AI tool = 1) as the independent variable revealed that the perceived realism of the shopping scenario was not significantly different between the experimental conditions ($M_{\text{self-reported questionnaire}}$ = 6.29, *SD* = .87 vs. $M_{\text{AI tool}}$ = 6.17, *SD* = .99; $F(1, 147) = .66$, $p > .40$, $\eta^2 = .004$). Furthermore, mean perceived realism of the shopping experience (*M* = 6.23, *SD* = .93) was significantly higher than the scale midpoint ($t_{148} = 29.2$, $p < .001$). The results with the realism of the shopping scenario were identical in the following experiments; hence, they are not presented for brevity.

Purchase Intentions We predicted that participants in the AI tool condition would report lower purchase intentions than those in the self-reported questionnaire condition (H_{1a}). A single-factor ANOVA revealed a significant main effect of shopping assistant (self-reported questionnaire = –1, AI tool = 1) on purchase intentions such that participants in the AI tool condition (*M* = 4.90, *SD* = 1.45) reported significantly lower purchase intentions than those in the self-reported condition (*M* = 5.33, *SD* = 1.06; $F(1, 147) = 4.14$, $p = .044$, $\eta^2 = .03$). This finding supports our main prediction (H_{1a}).

Satisfaction. We predicted that participants who used the AI tool would have lower satisfaction than those who used the self-reported questionnaire (H_{1b}). A single-factor ANOVA with shopping assistant (self-reported questionnaire = –1, AI tool = 1) as the independent variable and satisfaction as dependent variable revealed a significant main effect ($F(1, 147) = 5.76$, $p = .018$, $\eta^2 = .04$). In support of our hypothesis (H_{1b}), participants in the AI tool condition ($M = 5.35$, $SD = 1.23$) reported lower satisfaction with the shopping experience than participants in the self-reported questionnaire condition ($M = 5.79$, $SD = .97$).

Discussion

Experiment 1 showed that digital shopping assistant significantly influences consumers' purchase intentions and satisfaction. Specifically, participants who imagined using the AI tool reported significantly lower purchase intentions and satisfaction than those who imagined using the self-reported questionnaire, supporting our initial hypothesis (H_{1a} and H_{1b}). These findings align with past research suggesting that consumers tend to prefer human-centered shopping assistants when receiving personalized recommendations (Barari et al., 2024; Jussupow et al., 2020) while extending these findings the emerging context of AI diagnostic tools, beyond conventional recommendation systems. Although the results lend initial support to our predictions, the mechanism underlying the effect of shopping assistant remained unanswered. In the following experiment, we build on these findings and examine the role of perceived control and perceived personalization in driving this effect.

Experiment 2

Experiment 2 examines the mediating effect of perceived control and perceived personalization on the relation between shopping assistant and purchase intentions and satisfaction. Given the design of the AI diagnostic tool, characterized by lower user involvement, limited understanding, and potentially fostering feelings of uniqueness neglect (Barari et al., 2024; Franke et al., 2009; Longoni et al., 2019), we expect this AI tool to lead to lower perceived control and perceived personalization. Since lower perceived control and personalization are linked to decreased trust, satisfaction, and purchase intentions (Dabholkar & Sheng, 2012; Franke et al., 2009). We therefore hypothesized that the negative impact of the AI diagnostic tool (vs. self-reported questionnaire) on purchase intentions and satisfaction will be mediated by perceived control and perceived personalization (H_{2a} and H_{2b}).

Method

One hundred twenty-two participants who identify as female (M_{age} = 46.84, *SD* = 15.47) were recruited from MTurk to complete the experiment with a single-factor between-participants design (shopping assistant: self-reported questionnaire, AI tool). The procedure was similar to Experiment 1 with minor changes. As in Experiment 1, participants were asked to imagine using either the self-reported questionnaire or the AI tool as a shopping assistant while shopping for a new skincare routine. In both conditions, participants were presented with the same information and instructions about the shopping assistant from Experiment 1. The main difference in Experiment 2 was that participants were asked to complete scales measuring perceived control and perceived personalization before they were presented with the recommendations. Specifically, right after imagining using the shopping assistant, participants were told that they would receive a recommendation for a skincare routine based on the answers they provided to the questions (self-reported questionnaire condition) or the skin report developed using the selfie they uploaded (AI tool condition) and were asked to complete the scales measuring mediators prior to receiving the recommendation. Perceived control was measured using four items adapted from perceived control scales used in prior research ("*I would feel like I had control over how the product recommendations that I would receive are generated*"; 1 = strongly disagree, 7 = strongly agree; α = .93; adapted from Degachi et al., 2023; Hu & Wise, 2021; Rohden & Espartel, 2024). Perceived personalization was measured using three items ("*To what extent would you think the product recommendation would be [...] specifically tailored to your needs*"; 1 = strongly disagree, 7 = strongly agree; α = .95; adapted from Wang et al. 2025). Next, participants were presented with the same three skincare products, indicated their purchase intentions for each ($\alpha_{product\ 1}$ = .98, $\alpha_{product\ 2}$ =

.97, $\alpha_{product\ 3}$ = .99), and their satisfaction with the shopping experience (α = .98) using the same items as for Experiment 1. Finally, the study ended with the demographic variables.

Results

Three participants who did not finish the survey properly were excluded from the analyses, which were conducted on a sample of 119 participants (M_{age} = 47.2, *SD* = 15.02).

Purchase Intentions. We predicted that participants in the AI tool condition would have lower purchase intentions than those who used the self-reported questionnaire. A single-factor ANOVA revealed that participants in the AI tool condition reported significantly lower purchase intentions than those in the self-reported questionnaire condition ($M_{\text{AI tool}}$ = 4.66, *SD* = 1.56 vs. $M_{\text{self-reported questionnaire}}$ = 5.52, *SD* = 1.15; $F(1, 117) = 11.66$, $p < .001$, $\eta^2 = .09$), replicating the effect observed in Experiment 1.

We tested the role of perceived control[3] in driving the shopping assistant effect in a mediation analysis using PROCESS Model 4 with 5,000 bootstrap samples (Hayes, 2018). The results revealed a significant indirect effect of shopping assistant (self-reported questionnaire = –1, AI tool = 1) on purchase intentions through perceived control (b_{indirect} = –.47, *SE* = .11, 95% *CI* = [–.68; –.28]), while its direct effect was not significant (*b* = .04, *SE* = .13; *t* = .26, *p* = .79), suggesting an indirect-only mediation and lending initial support to our prediction (H_{2a}).

Next, we repeated the same analysis with perceived personalization[4] as the mediator (model 4, 5,000 bootstrap samples, Hayes 2018). The indirect effect of shopping assistant (self-reported questionnaire = –1, AI tool = 1) on purchase intentions through perceived personalization was significant (b_{indirect} = –.35, *SE* = .09, 95% *CI* = [–.53; –.20]), while its direct effect disappeared (*b* = –.08, *SE* = .11; *t* = –.75, *p* = .46), suggesting an indirect-only mediation and lending initial support to our prediction (H_{3a}).

[3] An ANOVA revealed a main effect of shopping assistant on perceived control ($M_{\text{AI tool}}$ = 4.00, *SD* = 1.54 vs. $M_{\text{self-reported questionnaire}}$ = 5.73, *SD* = .89; $F(1, 117) = 55.84$, $p < .001$, $\eta^2 = .32$).
[4] An ANOVA revealed a main effect of shopping assistant on perceived personalization ($M_{\text{AI tool}}$ = 4.94, *SD* = 1.36 vs. $M_{\text{self-reported questionnaire}}$ = 5.83, *SD* = .71; $F(1, 117) = 19.80$, $p < .001$, $\eta^2 = .15$).

Finally, and more importantly, we conducted parallel mediation analysis using PROCESS (model 4, 5,000 bootstrap samples, Hayes 2018), where perceived control and perceived personalization were parallel mediators. The results revealed a significant total indirect effect of shopping assistant (self-reported questionnaire = –1, AI tool = 1) on purchase intentions through perceived control and perceived personalization (b_{indirect} = –.34, *SE* = .10, 95% *CI* = [–.56; –.15]). However, this indirect effect was mainly driven by perceived personalization rather than perceived control. Specifically, when the two mediators were included in the model as parallel mediators, the indirect effect of the shopping assistant through perceived personalization remained significant (b_{indirect} = –.36, *SE* = .11, 95% *CI* = [–.60; –.16]), while its indirect effect through perceived control was not significant (b_{indirect} = .01, *SE* = .13, 95% *CI* = [-.26; .25]). These findings indicate that while perceived control and personalization are important psychological mechanisms, perceived personalization predominantly drives the negative effect of the AI diagnostic tool on purchase intentions. This supports prior research highlighting the central role of feeling understood and individually addressed in AI interactions (Barari et al., 2024; Longoni et al., 2019), particularly in emotionally involved contexts like skincare. We further elaborate on the implications of perceived personalization's dominant role in the discussion of this experiment.

Satisfaction. We predicted that participants in the AI tool condition would have lower satisfaction than those who used the self-reported questionnaire. A single-factor ANOVA with shopping assistant (self-reported questionnaire = –1, AI tool = 1) as the independent variable and satisfaction as the dependent variable supported this prediction: participants in the AI tool condition (*M* = 4.84, *SD* = 1.64) reported lower satisfaction with the shopping experience than participants in the self-reported questionnaire condition (*M* = 5.75, *SD* = 1.13; *F*(1, 117) = 12.40, *p* = < .001, η^2 = .10), replicating the effect observed in Experiment 1.

We tested the role of perceived control as a mediator driving the shopping assistant effect (model 4, 5,000 bootstrap samples, Hayes 2018). The results indicated a significant indirect effect of shopping assistant (self-reported questionnaire = –1, AI tool = 1) on satisfaction through perceived control (b_{indirect} = –.64, *SE* = .12, 95% *CI* = [–.89; –.43]), while its direct effect disappeared (b = .18, SE = .12; t = 1.53, p = .129). This finding suggests an indirect-only mediation, supporting our prediction (H_{2b}).

We repeated the analysis with perceived personalization as the mediator (model 4, 5,000 bootstrap samples, Hayes 2018). We found that the indirect effect of shopping assistant (self-reported questionnaire = –1, AI tool = 1) on satisfaction through perceived personalization was significant ($b_{indirect}$ = –.42, SE = .10, 95% CI = [–.61; –.24]), without a significant direct effect (b = –.04, SE = .10; t = –.41, p = .683), suggesting an indirect-only mediation. These results support our prediction (H_{3b}).

Finally, a parallel mediation analysis was conducted using PROCESS (model 4, 5,000 bootstrap samples, Hayes, 2018). The analysis revealed a significant total indirect effect of shopping assistant (self-reported questionnaire = –1, AI tool = 1) on satisfaction through perceived control and perceived personalization ($b_{indirect}$ = –.53, SE = .11, 95% CI = [–.77; –.32]). Specifically, shopping assistant had a significant indirect effect through perceived control ($b_{indirect}$ = –.22, SE = .12, 95% CI = [–.47; –.01]) and perceived personalization ($b_{indirect}$ = –.31, SE = .10, 95% CI = [–.52; –.14]). However, the direct effect of the shopping assistant on satisfaction was not significant when the mediators were included in the model (b = .07, SE = .11; t = .68, p = .496), suggesting an indirect-only mediation. In the case of purchase intentions, only perceived personalization showed a significant indirect effect when both mediators were included in a parallel mediation analysis. However, for satisfaction, both mediators were significant, though perceived personalization once again demonstrated a stronger influence, as indicated by a larger effect size (–.31 vs. –.22) and a more robust confidence interval. These results underscore the consistently dominant role of perceived personalization over perceived control, a point further explored in the discussion section.

Discussion

Experiment 2 tested whether the effect of shopping assistant on purchase intentions and satisfaction is driven by perceived control and perceived personalization. The results revealed that both perceived control and perceived personalization significantly mediated the effect of shopping assistant on purchase intentions and satisfaction. Specifically, participants in the AI tool condition reported significantly lower perceived control and perceived personalization, which in turn led to lower purchase intentions and satisfaction, providing initial support to our hypothesis (H_2 and H_3). For both dependent variables, the direct effect disappeared when the mediators were introduced, suggesting indirect-only mediations.

Unexpectedly, the parallel mediation analysis revealed that perceived personalization was the stronger driver of the mediation, suggesting that even though perceived control contributes to the shopping experience, perceived personalization has a greater impact on consumer outcomes in this digital shopping experience. Although this pattern was not initially hypothesized, a possible explanation may lie in the idea that, in emotionally involved contexts like skincare, consumers primarily seek reassurance that their unique needs are understood rather than need a perception of control over the process. When personalization reaches a sufficient level, it fulfills consumers' core expectations, making perceived control less relevant and increasing acceptance of the AI tool. In other words, if the recommendation aligns with consumers' expectations through a high degree of perceived personalization, consumers may place less relevance on how much influence they have over the generation of the recommendation. In sum, Experiment 2 confirmed the mediating role of both perceived control and perceived personalization in explaining the negative effect of AI diagnostic tools on consumer outcomes, with perceived personalization emerging as the stronger driver. In the following section, Experiment 3 examines whether enhancing perceived personalization by adding a measurement task can mitigate the negative effect of AI diagnostic tools and improve consumer responses.

Experiment 3

Having established in Experiment 2 that the negative effect of AI diagnostic tools on purchase intentions and satisfaction is mediated by both perceived control and perceived personalization, Experiment 3 examines a potential boundary condition for this effect. Prior research suggests that incorporating consumer input through a measurement task (i.e., contextual or preference-based questions) can enhance perceived personalization by making consumers feel that their unique needs are acknowledged (Kramer, 2007). We propose that adding a measurement task to the AI diagnostic process will restore perceived personalization and, in turn, mitigate the negative impact on consumer outcomes. Specifically, we expect this intervention to improve purchase intentions and satisfaction in the AI tool condition, while having minimal effect in the self-reported questionnaire condition, where consumer input is already present. Therefore, we hypothesize that the negative effect of the AI diagnostic tool will disappear when a measurement task is included, enhancing both consumer outcomes.

Method

One hundred thirty-five self-identified female participants (M_{age} = 43.51, *SD* = 12.68) recruited from MTurk completed the experiment that employed a 2 (shopping assistant: self-reported questionnaire, AI tool) × 2 (measurement task: absent, present) between-participants design. When the measurement task was absent, the shopping assistant conditions were identical to Experiment 2 (i.e., self-reported questionnaire – measurement task absent and AI tool – measurement task absent conditions). In the measurement task present conditions, however, we included a brief measurement task, which consists of four questions about the contextual elements in the consumers' environment ("*How much sleep do you usually get?*"; "*Do you often feel stressed or tense?*"; "*What is the weather like in your area most of the time?*"; "*Where do you live?*") to each shopping assistant (cf. Appendix A). In the self-reported questionnaire condition, these questions were added to the list of questions already existing in this shopping assistant. In the AI tool condition, participants imagined answering these questions right before participants were asked to imagine taking a selfie. As in Experiment 2, participants were then asked to indicate their level of perceived control (α = .92) and perceived personalization (α = .92) before receiving their recommendations using the same items from Experiment 2. Next, regardless of the condition, participants were presented with the same three products as in Experiment 1 and Experiment 2 and indicated their purchase intentions ($\alpha_{product\ 1}$ = .97, $\alpha_{product\ 2}$ = .97, $\alpha_{product\ 3}$ = .96) and satisfaction[5] (α = 98) with the shopping experience

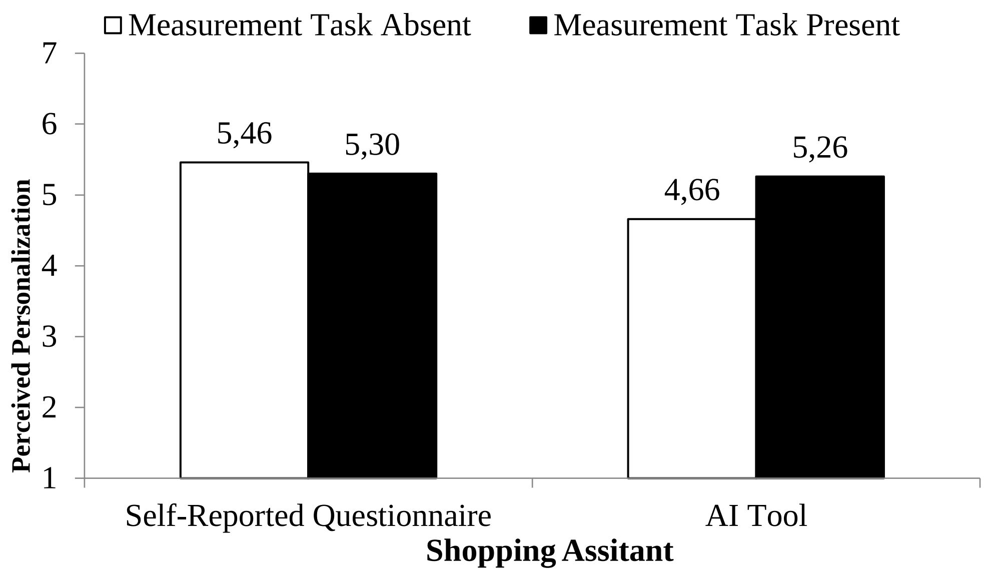
[5] Results with satisfaction followed a very similar pattern to those with purchase intentions. For brevity and to avoid repetition, results with satisfaction are presented in Appendix C.

using the same items. Finally, participants were asked to complete a series of demographic questions.

Results

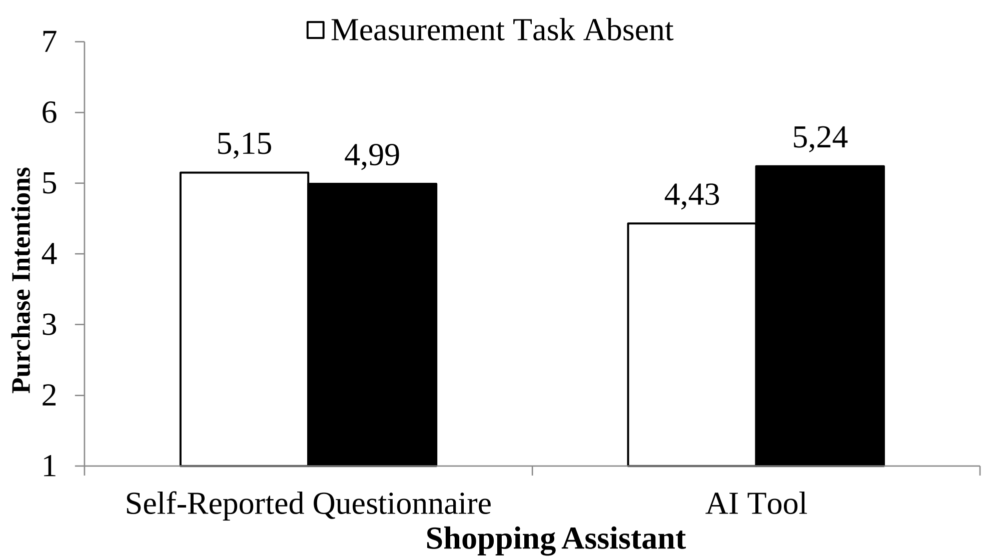
Perceived Personalization. In this section, we examine whether the presence of a measurement task mitigates the lower perceived personalization typically observed in the AI tool condition (vs. self-reported questionnaire). Given the autonomous nature of AI diagnostic tools, we predicted that adding a measurement task (i.e., contextual questions) would make consumers feel that their unique needs are acknowledged, thereby increasing perceived personalization (Kramer, 2007). Therefore, when the measurement task is absent, we expect participants to report lower perceived personalization in the AI tool condition (vs. the self-reported questionnaire). However, this difference should disappear when the measurement task is present. We anticipate this effect to be stronger in the AI tool condition, where consumer input is minimal compared to the self-reported questionnaire condition, which already engages participants through direct preference elicitation. To test these predictions, we conducted an ANOVA with shopping assistant (self-reported questionnaire = –1, AI tool = 1) and measurement task (absent = –1, present = 1) as independent variables and perceived personalization as the dependent variable. The analysis revealed a significant main effect of shopping assistant ($M_{\text{AI tool}}$ = 4.94, *SD* = 1.21 vs. $M_{\text{self-reported questionnaire}}$ = 5.38, *SD* = 1.01; $F(1, 131) = 4.96$, $p = .028$, $\eta^2 = .037$), and a significant shopping assistant × measurement task interaction ($F(1, 131) = 4.03$, $p = .047$, $\eta^2 = .030$). When the measurement task was absent, participants in the AI tool condition reported significantly lower perceived personalization than participants in the self-reported condition ($M_{\text{AI tool}}$ = 4.66, *SD* = 1.33 vs. $M_{\text{self-reported questionnaire}}$ = 5.46, *SD* = 1.16; $F(1, 131) = 9.33$, $p = .003$, $\eta^2 = .066$). When the measurement task was present, however, there were no significant differences in the two shopping assistant conditions ($M_{\text{AI tool}}$ = 5.26, *SD* = .99 vs. $M_{\text{self-reported questionnaire}}$ = 5.30, *SD* = .84; $F(1, 131) = .02$, $p > .80$; $\eta^2 = .00$) Additionally, in the AI tool condition, perceived personalization was significantly lower when the measurement task was absent (*M* = 4.66, *SD* = 1.33) than when it was present (*M* = 5.26, *SD* = .99; $F(1, 131) = 4.71$, $p = .032$, $\eta^2 = .035$). In contrast, in the self-reported questionnaire condition, there were no significant differences between the absence and presence of the measurement task (M_{absent} = 5.46, *SD* = 1.16 vs. $M_{present}$ = 5.30, *SD* = .84; $F(1, 131) = .38$, $p = .583$, $\eta^2 = .003$). These results support our theorizing that adding a measurement task increases perceived personalization in the AI tool condition but not in the self-reported questionnaire condition (see Figure 2).

Figure 2 – The Effect of Shopping Assistant on Perceived Personalization as a Function of Measurement Task, Experiment 2



Purchase Intentions. Next, we examine whether the presence of a measurement task mitigates the negative effect of the AI diagnostic tool on purchase intentions (vs. self-reported questionnaire). Given that lower perceived personalization is linked to reduced purchase intentions (Dabholkar & Sheng, 2012; Franke et al., 2009), we predicted that adding a measurement task (i.e., contextual questions) would enhance participants' perceived personalization and, in turn, improve purchase intentions (Kramer, 2007). Therefore, when the measurement task is absent, we expect participants using the AI tool to report lower purchase intentions compared to those using the self-reported questionnaire. However, this negative effect should disappear when the measurement task is present. We anticipate that this effect will be stronger in the AI tool condition, where consumer input is minimal compared to the self-reported questionnaire condition, which already engages participants through direct preference elicitation. To test these predictions, we conducted an ANOVA with shopping assistant (self-reported questionnaire = –1, AI tool = 1) and measurement task (absent = –1, present = 1) as independent variables and purchase intentions as the dependent variable. The analysis revealed only a significant shopping assistant × measurement task interaction ($F(1, 131) = 4.99$, $p = .027$, $\eta^2 = .037$). When the measurement task was absent, participants in the AI tool condition reported significantly lower purchase intentions than those in the self-reported questionnaire ($M_{\text{AI tool}} = 4.43$, $SD = 1.55$ vs. $M_{\text{self-reported questionnaire}} = 5.15$, $SD = 1.18$; $F(1, 131) = 5.73$, $p = .018$, $\eta^2 = .042$). When the measurement task was present, there were no significant differences between the two conditions ($M_{\text{AI tool}} = 5.24$, $SD = .88$ vs. $M_{\text{self-reported questionnaire}} = 4.99$, $SD = 1.28$; $F(1, 131) = .63$, $p > .40$, $\eta^2 = .005$). Additionally, in the AI tool condition, purchase intentions were significantly lower when the measurement task was absent than when it was present ($M_{\text{absent}} = 4.43$, $SD = 1.55$ vs. $M_{\text{present}} = 5.24$, $SD = .88$; $F(1, 131) = 6.46$, $p = .012$, $\eta^2 = .047$). However, in the self-reported questionnaire condition, there were no significant differences between the absence and presence of the measurement task ($M_{\text{absent}} = 5.15$, $SD = 1.18$ vs. $M_{\text{present}} = 4.99$, $SD = 1.28$; $F(1, 131) = .30$, $p > .50$, $\eta^2 = .002$). These findings are consistent with our predictions (H_{4a}) and are illustrated in Figure 3.

Figure 3 – The Effect of Shopping Assistant on Purchase Intentions as a Function of Measurement Task, Experiment 2



Then, we conducted a moderated mediation analysis using PROCESS (model 8, 5,000 bootstrap samples, Hayes, 2018) in which shopping assistant (self-reported questionnaire = –1, AI tool = 1) was entered as the independent variable, perceived personalization as the mediator, measurement task (absent = –1, present = 1) as the moderator, and purchase intentions as the dependent variable. This model tested whether the indirect effect of the shopping assistant on purchase intentions through perceived personalization depends on the inclusion of a measurement task. When the measurement task was absent, the indirect effect of the shopping assistant through perceived personalization was significant (b_{indirect} = –.27, *SE* = .11, 95% *CI* [–.50; –.07]), while its direct effect disappeared (*b* = –.09, *SE* = .13, 95% *CI* [–.34; .16]). When the measurement task was present, the indirect effect of the shopping assistant on purchase intentions through perceived personalization disappeared (b_{indirect} = –.01, *SE* = .08, 95% *CI* [–.15; .15]). Finally, we obtained a statistically significant index of moderated mediation (b_{index} = .25, *SE* = .14, 95% *CI* = [.010; .553]).

Finally, we conducted a moderated parallel mediation analysis using PROCESS (model 8, 5,000 bootstrap samples, Hayes 2018) to examine whether the indirect effect of TOOL on purchase intention through perceived control and perceived personalization was moderated by the presence of the measurement task. We entered shopping assistant (self-reported questionnaire = –1, AI tool = 1) as the independent variable, perceived control and perceived personalization as parallel mediators, measurement task (absent = –1, present = 1) as the moderator, and purchase intentions as the dependent variable. When the measurement task was absent, the indirect effect of the shopping assistant was significant through perceived control (b_{indirect} = –.12, *SE* = .06, 95% *CI* [–.26; –.02]) and perceived personalization (b_{indirect} = –.19, *SE* = .08, 95% *CI* [–.38; –.05]), while its direct effect disappeared (*b* = –.05, *SE* = .13, 95% *CI* [–.30; .20]), in line with the results of the previous studies. However, when the measurement task was present, the indirect effect of the shopping assistant on purchase intentions through perceived control (b_{indirect} = –.08, *SE* = .05, 95% *CI* [–.189; .003]) and perceived personalization (b_{indirect} = –.01, *SE* = .05, 95% *CI* [–.11; .10]) was not significant. Importantly, in line with the previous experiment, we obtained a statistically significant index of moderated mediation through perceived personalization (b_{index} = .18, *SE* = .10, 95% *CI* [.01; .42]), but not through perceived control (b_{index} = .04, SE = .06, 95% CI = [–.06; .20]). Together, these analyses provide strong support for H_{4a}.

Discussion

Experiment 3 tested whether the inclusion of a measurement task (i.e., the addition of contextual questions) moderates the effects of shopping assistant on perceived personalization, and then on purchase intentions and satisfaction. As hypothesized (H_4), we observed a significant shopping assistant x measurement task interaction for all three variables. When the measurement task was absent, participants in the AI tool condition reported significantly lower perceived personalization, purchase intentions and satisfaction than those in the self-reported condition. However, when the measurement task was present, there was no significant difference between the two conditions (shopping assistant: self-reported questionnaire, AI tool) for all three variables. Moreover, within the AI tool condition, participants reported significantly lower perceived personalization, purchase intentions, and satisfaction when the measurement task was absent compared to when it was present. In contrast, the presence of the measurement task had no significant effect in the self-reported questionnaire condition, suggesting that adding a measurement task (i.e., contextual questions) in the AI tool condition helps compensate for the perceived lack of consideration of consumers' preferences and needs, whereas, for the self-reported questionnaire, the measurement task likely provided little additional benefit, as participants' expectations for personalization were already met. The moderated mediation analyses further supported our predictions (H_4). When the measurement task was absent, the effects of shopping assistant on both purchase intentions and satisfaction were mediated by perceived personalization, and perceived control. In contrast, these indirect effects disappeared when the measurement task was present. Interestingly, we only obtained statistically significant indexes of moderated mediation for perceived personalization (and not for perceived control), confirming that the addition of a measurement task enhances the perceived personalization of AI recommendations systems, thereby mitigating the negative effects associated with AI tools. This finding reinforces the dominant role of perceived personalization in driving consumer responses to AI diagnostic tools, an effect already observed in Experiment 2, where perceived personalization consistently emerged as the stronger mediator. Together, these results suggest that while both perceived control and perceived personalization contribute to the consumer experience, enhancing perceived personalization is particularly effective in mitigating the negative impact of AI tools. This highlights the importance of addressing personalization perceptions when designing AI recommendation systems. As demonstrated in Experiment 3, restoring a sense of being understood through the inclusion of a measurement task can significantly improve consumer acceptance and outcomes in AI tools. Overall, these findings provide a comprehensive understanding of how perceived personalization can be leveraged to overcome the limitations of AI diagnostic tools. The following section presents the general discussion, highlighting the theoretical insights, practical applications, and limitations of this research.

Chapter 5: General Discussion

Summary of Findings

This research investigates how consumers respond to AI diagnostic tools compared to more conventional recommendation systems, such as self-reported questionnaires, in the context of skincare. In line with our research question, we aimed to understand how these digital shopping assistants shape consumer experience, particularly regarding purchase intentions and satisfaction with the shopping experience. In a series of experimental studies, we show a negative effect of the AI diagnostic tool (vs. self-reported questionnaire) on both purchase intentions and satisfaction with the shopping experience in support of H_{1a} and H_{1b} (Experiment 1), indicating that consumers initially prefer human-centered systems over AI tools. We demonstrate that the negative effect of AI diagnostic tool (vs. self-reported questionnaire) is driven by lower perceptions of control and personalization, lending support to the mediating roles proposed in H_2 and H_3 (Experiment 2). Importantly, perceived personalization had a more robust influence on purchase intentions and satisfaction. Finally, we identify a boundary condition revealing that the negative effect of AI diagnostic tool (vs. self-reported questionnaire) on purchase intentions and satisfaction disappears when a measurement task (i.e., a series of contextual questions) is included in the shopping assistant, in support of H_4 (Experiment 3). This finding suggests that the perceived lack of personalization associated with AI tools can be mitigated through design interventions that increase perceived personalization, leading to enhanced purchase intentions and satisfaction. Taken together, these results provide an initial understanding of the impact of AI diagnostic tools on consumer experience in terms of purchase intentions and satisfaction with the shopping experience.

An unexpected result observed in our research was that perceived personalization emerged as a stronger driver of the negative effect of AI diagnostic tool (vs. self-reported questionnaire) on purchase intentions and satisfaction compared to perceived control. Specifically, in Experiment 2, when we included perceived personalization and perceived control in a PROCESS model as parallel mediators, the indirect effect of shopping assistant on purchase intentions through perceived personalization was significant, while its indirect effect through perceived control disappeared (these variables mediated the effect of shopping assistant on purchase intentions when they served as the only mediator in separate PROCESS models). We interpret these results as when personalization needs are fulfilled, consumers feel the recommendations reflect their unique concerns and perceived control becomes less relevant to the overall experience. In other words, feeling understood may outweigh the need to feel in control for emotionally involved categories like skincare. This interpretation aligns well with prior research, which suggests that when personalization is high, consumers may become more accepting of automation (Franke et al., 2009; Kramer, 2007). Furthermore, it is in line with past research suggesting that in high-involvement and sensitive domains, consumers primarily seek reassurance that their unique needs are being understood and addressed (Dreno & Layton, 2021; Liang et al., 2006; Rodgers, 2023). Therefore, when the perceived personalization of the recommendations developed by an AI diagnostic tool achieves a certain threshold, it fulfills consumers' core expectations from the interaction with the shopping assistant, which is to receive a personalized recommendation, and perceived control becomes less essential to the process. In short, perceived personalization compensates for the absence of control, increasing consumers' acceptance of autonomous systems like AI diagnostic tools. We next present the theoretical and managerial implications of our findings and conclude with a discussion of the limitations of our research, which offer fruitful avenues for future research.

Theoretical Contributions

This research extends prior work on AI in marketing and consumer behavior, which has mainly focused on AI recommendation systems, by examining a novel AI tool that serves as a diagnostic tool (Ameen et al., 2021; Ebrahimi et al., 2022; Schepman & Rodway, 2023). Whereas AI recommendation systems tend to operate based on consumers past behavior or explicit preferences (Ansari et al., 2000; Li & Karahanna, 2015; O'Donovan & Smyth, 2005), AI diagnostic tools examined in this research autonomously evaluate consumers' condition and understand their needs through image analysis. Therefore, compared to previously studied AI recommendation systems, the AI diagnostic tool requires minimal consumer involvement and relies on a more objective information source (e.g., an image) rather than the information provided by consumers (e.g., past behavior, preferences, etc.). Given this distinction, it is important to understand how consumers react to this rather novel use of AI as a diagnostic tool. Therefore, the current research contributes to the emerging literature on how different types of AI influence consumer experience and decision-making processes (Glikson & Wolley, 2020; Guha et al., 2021; Kaplan et al., 2023), particularly within the novel context of AI diagnostic tools. Furthermore, this research demonstrates a negative consumer response to AI diagnostic tools compared to more conventional tools like self-reported questionnaires. This contributes to research on consumer reactions to AI by showing that, despite their growing prevalence, AI tools may still generate resistance (Barari et al., 2024; Dietvorst et al., 2015; Longoni & Cian, 2022; Riegger et al., 2021).

Our research further documents two psychological mechanisms underlying this resistance, demonstrating that the negative effect of AI tools (vs. self-reported questionnaire) is mediated by perceived control and perceived personalization (André et al., 2018; Franke et al., 2009; Komiak & Benbasat, 2006). More importantly, we offer a nuanced understanding of the mechanisms underlying the negative effect of AI tools (vs. self-reported questionnaire), showing that perceived personalization plays a more dominant role than perceived control. This extends prior literature examining the role of perceived personalization and perceived control in driving consumer reactions to AI tools (Ameen et al., 2021; André et al., 2018; Longoni et al., 2019), by suggesting a hierarchical relationship between the two constructs, where personalization needs when fulfilled, compensate for lower levels of perceived control.

Finally, we contribute to prior research by identifying a boundary condition to the negative effect of AI tools (vs, self-reported questionnaire), demonstrating that a measurement task (i.e., contextual questions) moderates the observed outcomes. Although previous research has established the value of measurement tasks for enhancing personalization (Franke et al., 2009; Kramer, 2007), our study extends this work by demonstrating that measurement tasks can be effectively integrated with AI tools. Similar to prior research that advocates hybrid models to increase consumer acceptance (Barari et al., 2024; Jussupow et al., 2020), our findings suggest that rather than viewing AI tools as alternatives to conventional tools such as self-reported questionnaires, they can be used complementarily. Specifically, incorporating a measurement task, such as explicit contextual or preferential questions commonly found in self-reported questionnaires, into the design of an AI tool can help restore consumers' perceptions of personalization, thereby enhancing both the acceptance and effectiveness of AI recommendations. Together, these contributions advance the theoretical understanding of AI diagnostic tools by highlighting how they differ from conventional recommendation systems, which psychological mechanisms shape consumer experience, and how their adverse effects can be mitigated through thoughtful design.

Managerial Implications

From a practical perspective, this research provides important insights for practitioners aiming to implement AI diagnostic tools into their customer journey, particularly in the skincare industry. First, our research offers a clearer understanding of how AI diagnostic tools function differently from conventional recommendation systems, and how these differences shape consumer reactions. Unlike tools that rely on explicit consumer input, Ai diagnostic tools operate more autonomously, often analyzing data such as images or biometric signals, making it harder for consumers to perceive how their needs are being translated into recommendations. While AI tools can be powerful personalization technologies, they must be deployed with care, as they may lead to negative consumer responses, such as reduced purchase intentions and satisfaction. Then, our findings underscore two significant psychological mechanisms: perceived control and perceived personalization, as central to consumers' acceptance of AI tools. Managers designing or selecting AI diagnostic tools should therefore be attentive to how these systems shape consumers' subjective experience of both control and personalization to ensure effectiveness. Our results show that consumers prefer tools that allow them to participate actively in the diagnostic and recommendation process. Thus, practitioners should not focus solely on technical accuracy but also ensure that consumers feel involved and understood. However, perceived personalization emerged as the more influential driver, suggesting that practitioners should prioritize interventions that reinforce the feeling that the system understands and reflects consumers' unique needs to effectiveness of the tool. To increase the effectiveness of AI tools, one practical intervention is the incorporation of a measurement task, such as a short set of contextual questions that allows consumers to provide relevant input. This simple design feature can significantly improve perceived personalization and, in turn, enhance behavioral outcomes. Finally, even in cases where AI is deployed in different industries or contexts, managers replacing more conventional and human-centered recommendation systems involving explicit consumer input (e.g., preference forms) with automated, factual inputs (e.g., biometric data or image analysis) should be cautious. Removing mechanisms like measurement tasks can unintentionally reduce perceived personalization. If not carefully addressed, this could weaken the effectiveness of AI recommendations, even when the underlying technology is advanced. For this reason, AI implementations should be complemented by design features that preserve the subjective feeling of being heard and understood. In sum, practitioners aiming to integrate AI diagnostic tools into the customer journey must consider not only technological sophistication but also thoughtful design that prioritizes the consumer's psychological experience, in order to reduce potential negative impacts. We next discuss the limitations and future research avenues.

Limitations & Future Research Avenues

As with any research, this study is subject to certain limitations that open avenues for further investigation. First, our experiments were scenario-based, which may limit the external validity of our findings, although participants in the experiments perceived the scenarios to be realistic. While this method allows for greater control and consistency, it does not fully reflect the complexity of real-world decision-making. In the specific case of AI diagnostic tools, we did not ask participants to upload their selfies for image-based analysis or interact with the tool in real-time. As a result, participants were only asked to imagine going through the experience, an approach that lacks the interactivity of actual usage. Future research should consider field studies or real-time consumer interactions with AI diagnostic tools to capture more authentic consumer reactions. Second, all experiments were conducted online and relied on self-reported data, which may be subject to biases, such as limited cognitive engagement. Using behavioral data, such as website clicks, purchase behavior, or observations from field studies, could provide a more robust understanding of how consumers respond to AI diagnostic tools. Third, the study sample was composed entirely of U.S.-based participants, which may limit the generalizability of findings to other cultural contexts. Future studies should explore cross-cultural differences, as attitudes toward AI diagnostic tools and perceptions of personalization may vary across cultures (Mehmood et al., 2024).

Beyond these limitations, several promising research directions emerge. One avenue involves examining individual difference variables, such as technological readiness, attitudes toward AI, preference for autonomy, or product involvement, which may moderate consumer reactions to AI diagnostic tools. Furthermore, understanding how these individual differences influence perceived personalization, and perceived control could help firms create more effective and targeted AI tools. In a similar vein, future research can examine generational differences in response to AI tools. As Priporas et al. (2017) note, Generation Z is particularly drawn to fast, easy, and autonomous shopping technologies. Examining how different generations respond to AI, especially novel technologies such as diagnostic tools, could help managers tailor experiences more effectively based on customer segments.

In addition, future research could explore alternative design elements to improve perceived personalization beyond measurement tasks. Design elements such as personalized communication styles, visual customization of outputs (e.g., tailored skincare reports), or transparency-enhancing explanations could enhance consumer experience and increase purchase intentions. Moreover, while our findings highlight that perceived personalization plays a more influential role than perceived control, the relationship between these two mechanisms deserves further investigation. Future research could explore whether perceived control becomes more important when personalization is low or examine the conditions under which the two factors may interact.

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Appendix

Appendix A: Experimental Manipulations and Stimuli

Experiment 1: AI Diagnostic Tool Condition

Shopping Simulation Task

In this study, we kindly invite you to go through a shopping simulation, which requires you to imagine yourself in the scenario described in the following pages and answer the questions that follow.

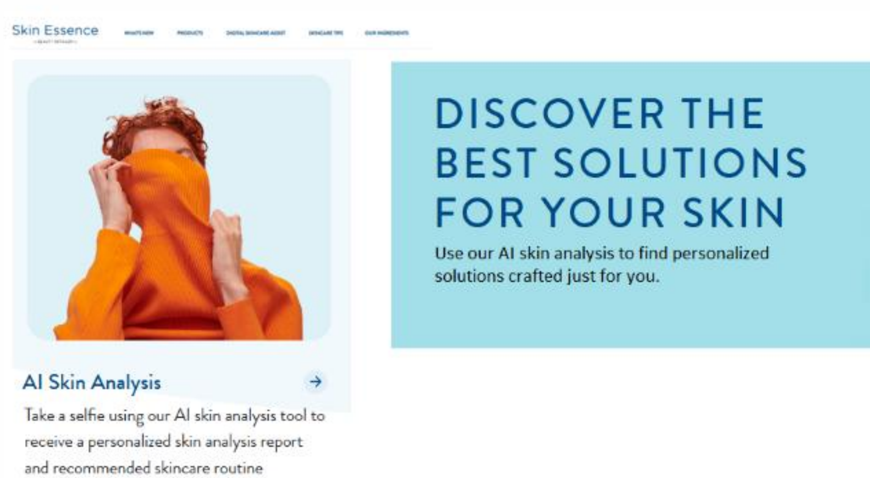
In the following screens, please read the scenario carefully and try to imagine yourself in the described situation as vividly as possible.

You can click next to begin.

------------ Page Break ------------

Imagine that you are looking for a **new** skincare routine and you visit the online store of Skin Essence, a skincare and beauty products retailer.

Upon landing on the main page of Skin Essence, you see the "AI Skin Analysis" tab, a digital shopping assistance tool, which entails taking a selfie for the skin analysis tool to receive a personalized skincare routine recommendation.



You decide to use the "AI Skin Analysis" and clicked on it.

------------ Page Break ------------

On the next page, you are presented with instructions to take the selfie and use the "Skin Essence AI Skin Analysis" tool.

AN AI-POWERED SKIN DIAGNOSIS DEVELOPED WITH DERMATOLOGISTS

GET YOUR MOST ACCURATE SKIN DIAGNOSIS IN 1 MINUTE. TAKE A SELFIE, GET YOUR SKIN ANALYSIS RESULTS AND A PERSONALIZED SKINCARE PROTOCOL.

95% ACCURACY TO DETECT SKIN STRENGTHS

OUR ALGORITHM IS BASED ON 20 YEARS OF SKIN RESEARCH AND TRAINED BY DERMATOLOGIST EVALUATIONS OF OVER 15,000 PHOTOS TO CALCULATE THE SCORE.

TAKE A SELFIE

For a perfect analysis, please follow the following guidelines:

- REMOVE MAKEUP AND GLASSES
- PULL YOUR HAIR BACK
- FACE CAMERA AND KEEP EXPRESSION NEUTRAL
- STAY IN WELL-LIT, NATURAL LIGHT

SKINCONSULT AI needs to access your camera to provide a personalized experience based on your selfie.
Your selfie will not be saved in our database.

TAKE A SELFIE

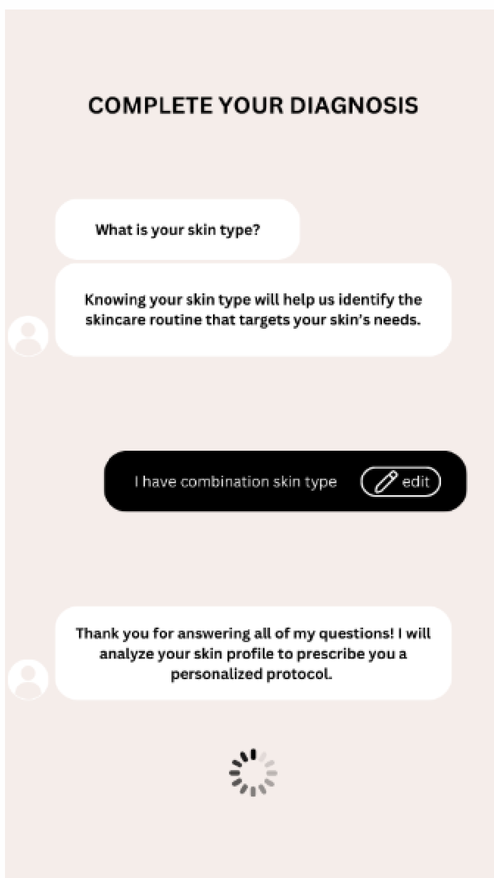
You click on "Take a Selfie".

------------ Page Break ------------

On the following page, you see the interface below to take a selfie for "Skin Essence AI Skin Analysis" tool to develop your skin report:

You take the selfie very easily and submit it for the skin analysis.

Finally, prior to your skin analysis report being developed, you answer a couple of quick questions:

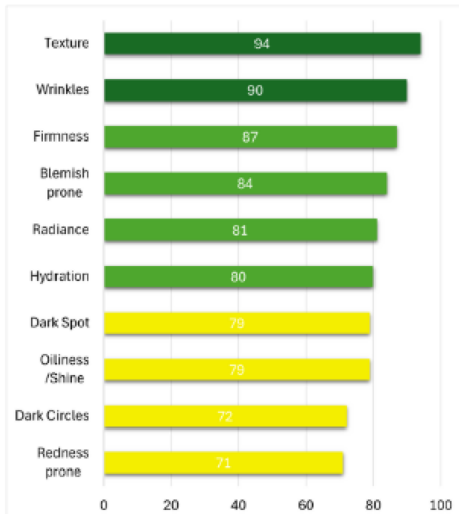


------------ Page Break ------------

Next, you are presented with the skin report from the AI skin analysis based on the selfie that you uploaded:

DISCOVER YOUR COMPLETE SKIN PROFILE

YOUR SKIN HEALTH RATE IS 81



THE SCALE FOR THE SKINCARE REPORT IS AS FOLLOWS:
100 - 90: PERFECT
89 - 80: GOOD
79 - 70: AVERAGE
69 - 50: POOR
49 - 0: VERY POOR

------------ Page Break ------------

On the following page, you receive a personalized recommendation for a skincare routine with three products. The recommended skincare routine is based on the skin analysis report from AI Skin Analysis tool:

YOUR PERSONALIZED SKINCARE SOLUTION IS HERE

CLEANSE

Typologie - Exfoliating Cleansing Gel
| 200ml

This gentle micro-exfoliating gel unclogs pores, smooths skin texture, and enhances radiance for a more even complexion. Suitable for all skin types, it transforms into a fine foam when massaged onto damp skin. 98% naturally derived and vegan.

TREAT

Bkind - Soothing Face Serum with Arnica & Hyaluronic Acid
| 48ml

The Soothing Face Serum calms redness and irritation, hydrates, and strengthens the skin barrier with anti-inflammatory and antioxidant ingredients. Its lightweight gel absorbs quickly, leaving skin soothed and ready for moisturizer. Natural, vegan, and recyclable packaging.

MOISTURIZE

Blume - Meltdown Gel Cream with Ceramides
| 50ml

This gel cream hydrates for 72 hours, perfect for all skin types, especially sensitive or acne-prone. With squalane, ceramides, and niacinamide, it plumps, calms, and brightens while protecting against blue light and pollution. Clean, vegan, and cruelty-free.

Imagining yourself in this shopping scenario, please answer the following questions

CLEANSE

Typologie - Exfoliating Cleansing Gel
| 200ml

This gentle micro-exfoliating gel unclogs pores, smooths skin texture, and enhances radiance for a more even complexion. Suitable for all skin types, it transforms into a fine foam when massaged onto damp skin. 98% naturally derived and vegan.

How likely would you be to purchase the recommended product presented above, if you found yourself in this situation?

	1	2	3	4	5	6	7	
Not likely at all	○	○	○	○	○	○	○	Very likely
Not probable at all	○	○	○	○	○	○	○	Very probable

TREAT

Bkind - Soothing Face Serum with Arnica & Hyaluronic Acid
| 48ml

The Soothing Face Serum calms redness and irritation, hydrates, and strengthens the skin barrier with anti-inflammatory and antioxidant ingredients. Its lightweight gel absorbs quickly, leaving skin soothed and ready for moisturizer. Natural, vegan, and recyclable packaging.

How likely would you be to purchase the recommended product presented above, if you found yourself in this situation?

	1	2	3	4	5	6	7	
Not likely at all	○	○	○	○	○	○	○	Very likely
Not probable at all	○	○	○	○	○	○	○	Very probable

MOISTURIZE

Blume - Meltdown Gel Cream with Ceramides
| 50ml

This gel cream hydrates for 72 hours, perfect for all skin types, especially sensitive or acne-prone. With squalane, ceramides, and niacinamide, it plumps, calms, and brightens while protecting against blue light and pollution. Clean, vegan, and cruelty-free.

How likely would you be to purchase the recommended product presented above, if you found yourself in this situation?

	1	2	3	4	5	6	7	
Not likely at all	○	○	○	○	○	○	○	Very likely
Not probable at all	○	○	○	○	○	○	○	Very probable

Please indicate the extent to which you agree or disagree with the statements below:

I would be...

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
Satisfied with the shopping experience.	○	○	○	○	○	○	○
Pleased with the shopping experience.	○	○	○	○	○	○	○
Happy with the shopping experience.	○	○	○	○	○	○	○

------------ Page Break ------------

Please indicate the extent to which you agree or disagree with the statements below:

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
The shopping experience I imagined going through in this survey could exist in reality as described.	◯	◯	◯	◯	◯	◯	◯
The purchase situation I imagined going through on a retailer's website in this survey was realistic.	◯	◯	◯	◯	◯	◯	◯
It was very easy for me to put myself into the shopping experience desribed in this survey.	◯	◯	◯	◯	◯	◯	◯

Experiment 1: Self-Reported Questionnaire Condition

Shopping Simulation Task

In this study, we kindly invite you to go through a shopping simulation, which requires you to imagine yourself in the scenario described in the following pages and answer the questions that follow.

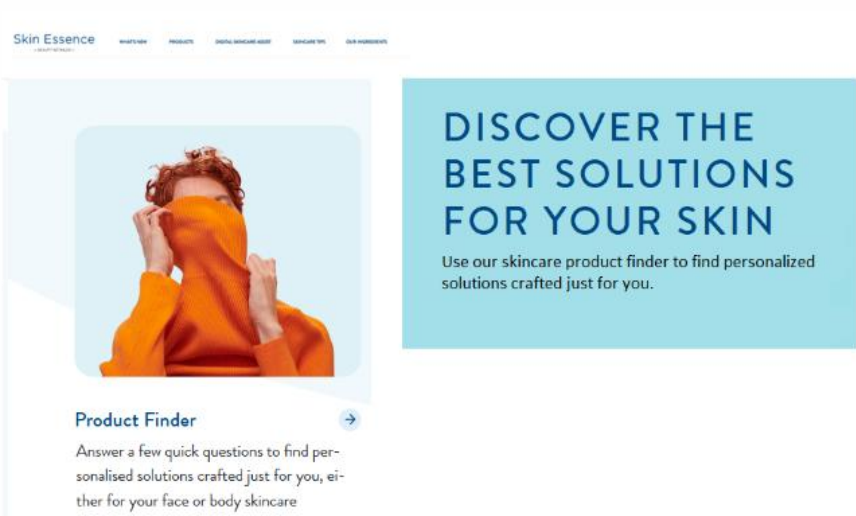
In the following screens, please read the scenario carefully and try to imagine yourself in the described situation as vividly as possible.

You can click next to begin.

------------ Page Break ------------

Imagine that you are looking for a **new** skincare routine and you visit the online store of Skin Essence, a skincare and beauty products retailer.

Upon landing on the main page of Skin Essence, you see the "Product Finder" tab, a digital shopping assistance tool, which entails answering a series of questions to receive a personalized skincare routine recommendation.



You decided to use the "Product Finder" tool and clicked on it.

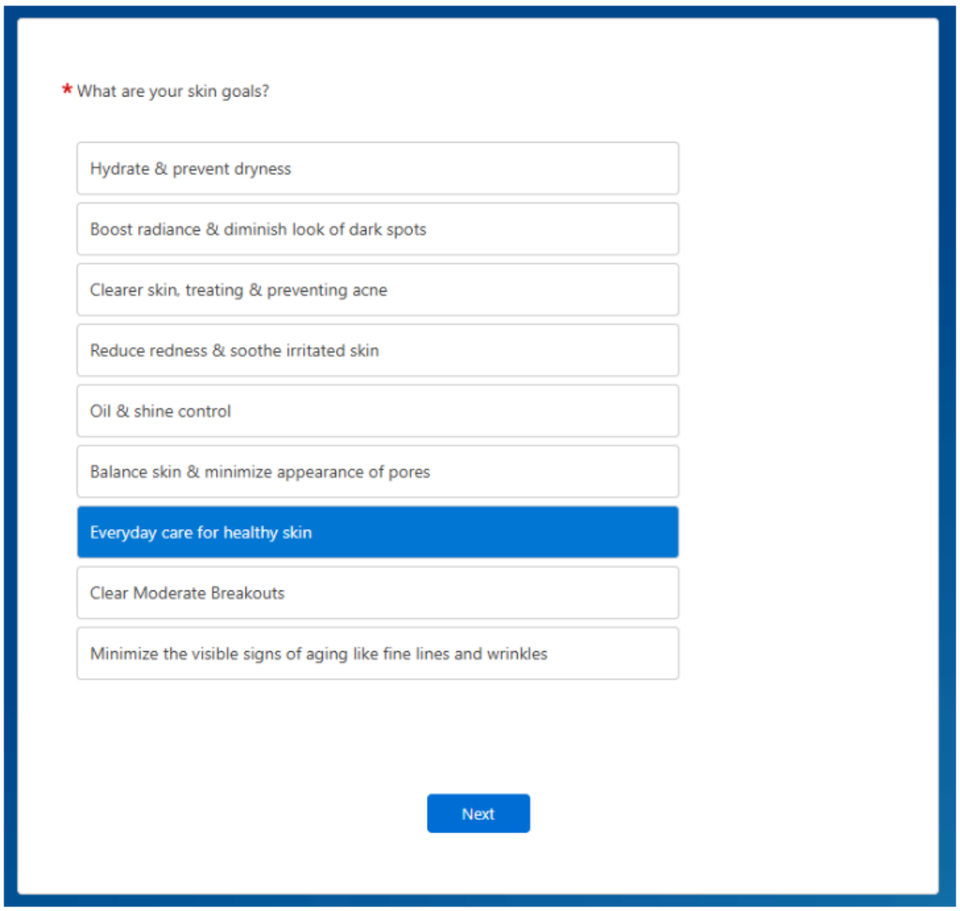
------------ Page Break ------------

The "Product Finder" tool then asks you to answer a series of questions.

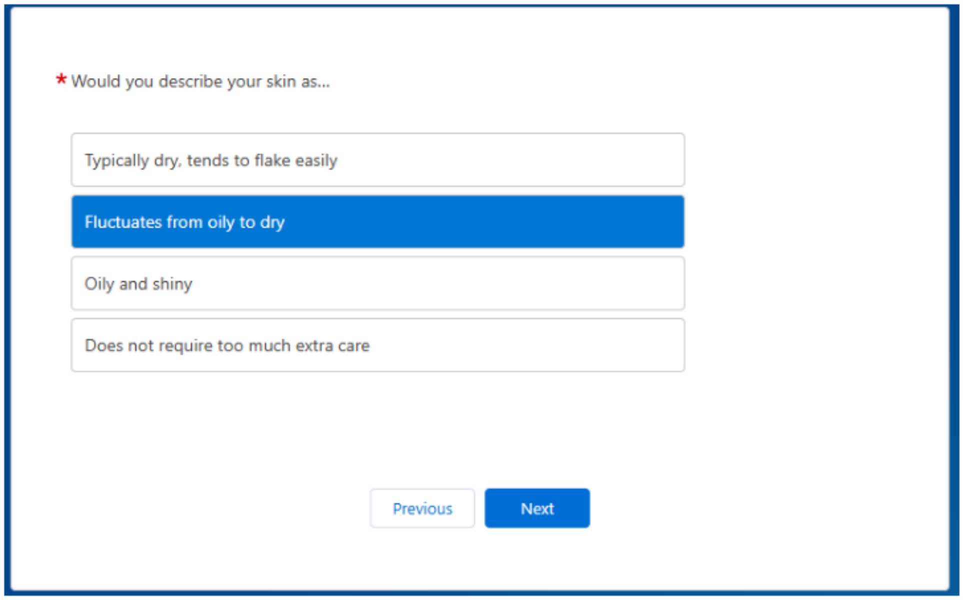
You answer the questions one by one and click next after answering each question.

Please see the questions and your answer to each question:

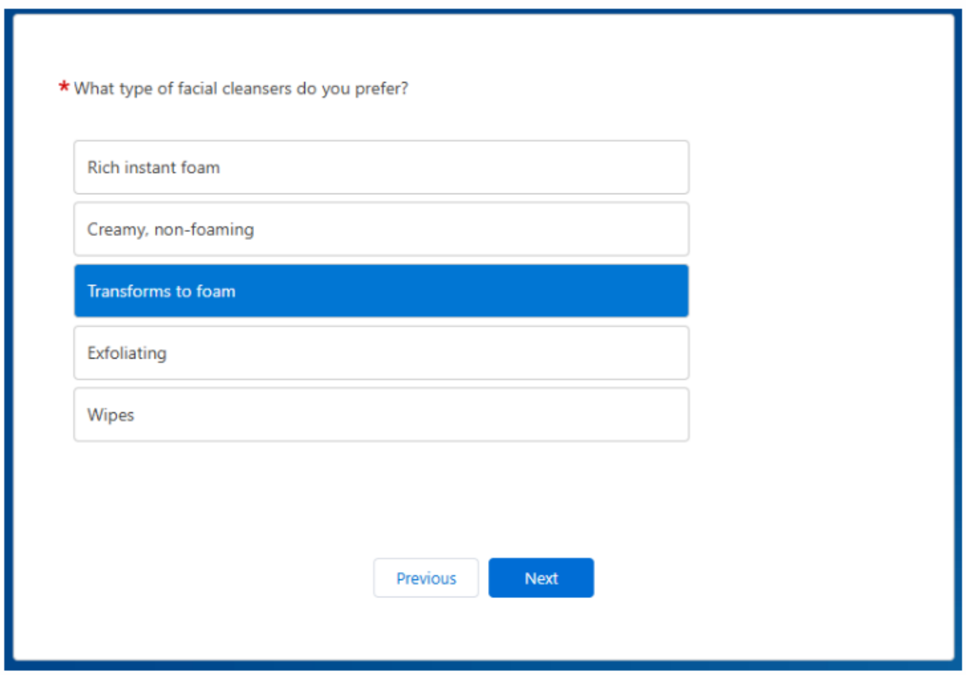
Question 1



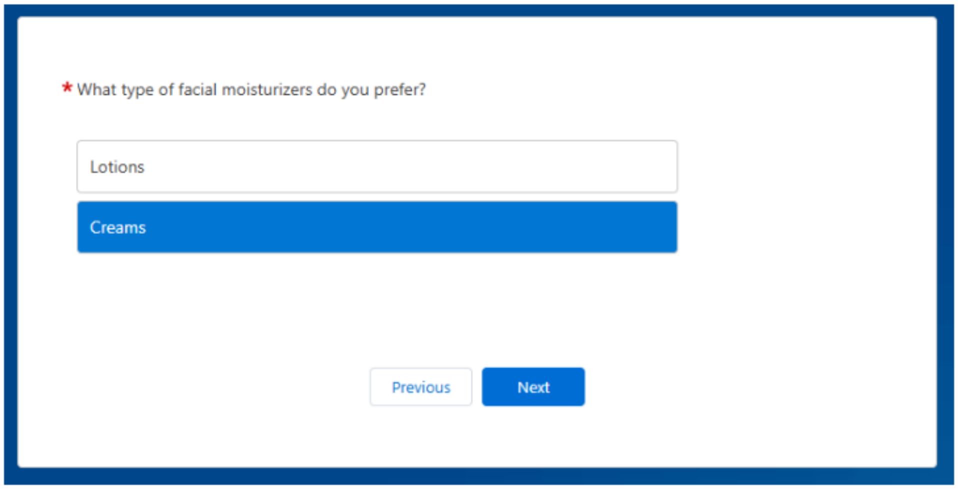
Question 2



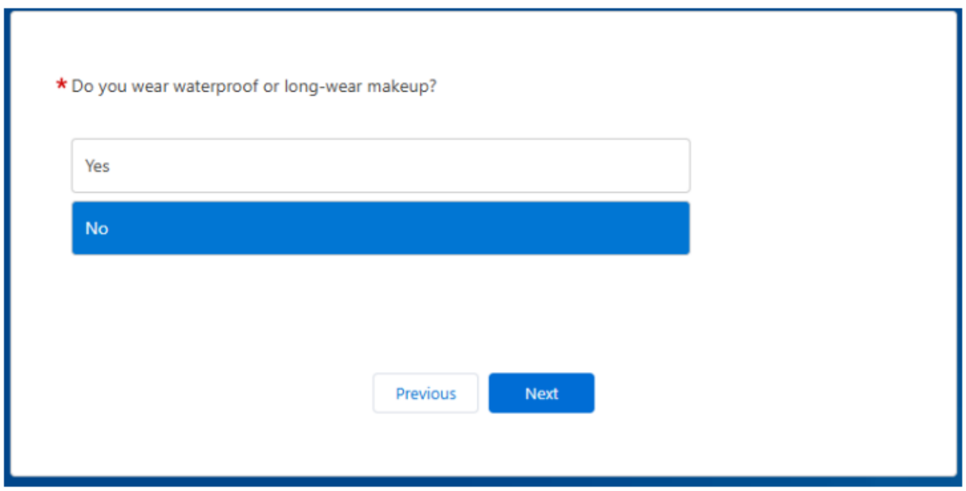
Question 3



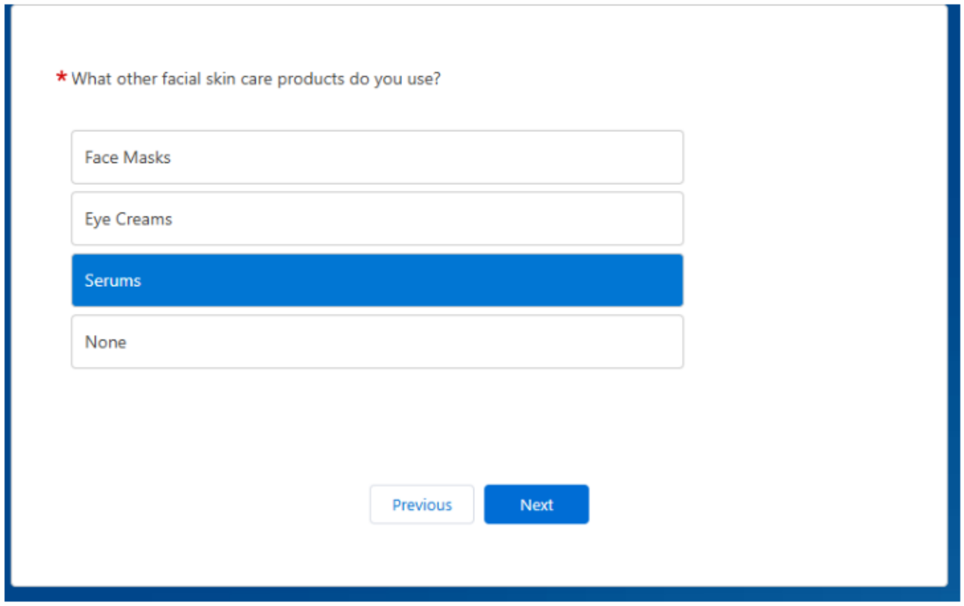
Question 4



Question 5



Question 6



Question 7 (The Last Question)

You answer the last question as "Somewhat sensitive" and clicks on "Finish".

------------ Page Break ------------

On the following page, you receive a personalized recommendation for a skincare routine with three products. The recommended skincare routine is based on the answers you provided to the questions from Product Finder tool:

YOUR PERSONALIZED SKINCARE SOLUTION IS HERE

CLEANSE

Typologie - Exfoliating Cleansing Gel
| 200ml

This gentle micro-exfoliating gel unclogs pores, smooths skin texture, and enhances radiance for a more even complexion. Suitable for all skin types, it transforms into a fine foam when massaged onto damp skin. 98% naturally derived and vegan.

TREAT

Bkind - Soothing Face Serum with Arnica & Hyaluronic Acid
| 48ml

The Soothing Face Serum calms redness and irritation, hydrates, and strengthens the skin barrier with anti-inflammatory and antioxidant ingredients. Its lightweight gel absorbs quickly, leaving skin soothed and ready for moisturizer. Natural, vegan, and recyclable packaging.

MOISTURIZE

Blume - Meltdown Gel Cream with Ceramides
| 50ml

This gel cream hydrates for 72 hours, perfect for all skin types, especially sensitive or acne-prone. With squalane, ceramides, and niacinamide, it plumps, calms, and brightens while protecting against blue light and pollution. Clean, vegan, and cruelty-free.

Imagining yourself in this shopping scenario, please answer the following questions

CLEANSE

Typologie - Exfoliating Cleansing Gel
| 200ml

This gentle micro-exfoliating gel unclogs pores, smooths skin texture, and enhances radiance for a more even complexion. Suitable for all skin types, it transforms into a fine foam when massaged onto damp skin. 98% naturally derived and vegan.

How likely would you be to purchase the recommended product presented above, if you found yourself in this situation?

	1	2	3	4	5	6	7	
Not likely at all	◯	◯	◯	◯	◯	◯	◯	Very likely
Not probable at all	◯	◯	◯	◯	◯	◯	◯	Very probable

TREAT

Bkind - Soothing Face Serum with Arnica & Hyaluronic Acid
| 48ml

The Soothing Face Serum calms redness and irritation, hydrates, and strengthens the skin barrier with anti-inflammatory and antioxidant ingredients. Its lightweight gel absorbs quickly, leaving skin soothed and ready for moisturizer. Natural, vegan, and recyclable packaging.

How likely would you be to purchase the recommended product presented above, if you found yourself in this situation?

	1	2	3	4	5	6	7	
Not likely at all	◯	◯	◯	◯	◯	◯	◯	Very likely
Not probable at all	◯	◯	◯	◯	◯	◯	◯	Very probable

MOISTURIZE

Blume - Meltdown Gel Cream with Ceramides
| 50ml

This gel cream hydrates for 72 hours, perfect for all skin types, especially sensitive or acne-prone. With squalane, ceramides, and niacinamide, it plumps, calms, and brightens while protecting against blue light and pollution. Clean, vegan, and cruelty-free.

How likely would you be to purchase the recommended product presented above, if you found yourself in this situation?

	1	2	3	4	5	6	7	
Not likely at all	○	○	○	○	○	○	○	Very likely
Not probable at all	○	○	○	○	○	○	○	Very probable

Please indicate the extent to which you agree or disagree with the statements below:

I would be...

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
Satisfied with the shopping experience.	○	○	○	○	○	○	○
Pleased with the shopping experience.	○	○	○	○	○	○	○
Happy with the shopping experience.	○	○	○	○	○	○	○

------------ Page Break ------------

Please indicate the extent to which you agree or disagree with the statements below:

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
The shopping experience I imagined going through in this survey could exist in reality as described.	○	○	○	○	○	○	○
The purchase situation I imagined going through on a retailer's website in this survey was realistic.	○	○	○	○	○	○	○
It was very easy for me to put myself into the shopping experience desribed in this survey.	○	○	○	○	○	○	○

Experiment 2: AI Diagnostic Tool Condition

Shopping Simulation Task

In this study, we kindly invite you to go through a shopping simulation, which requires you to imagine yourself in the scenario described in the following pages and answer the questions that follow.

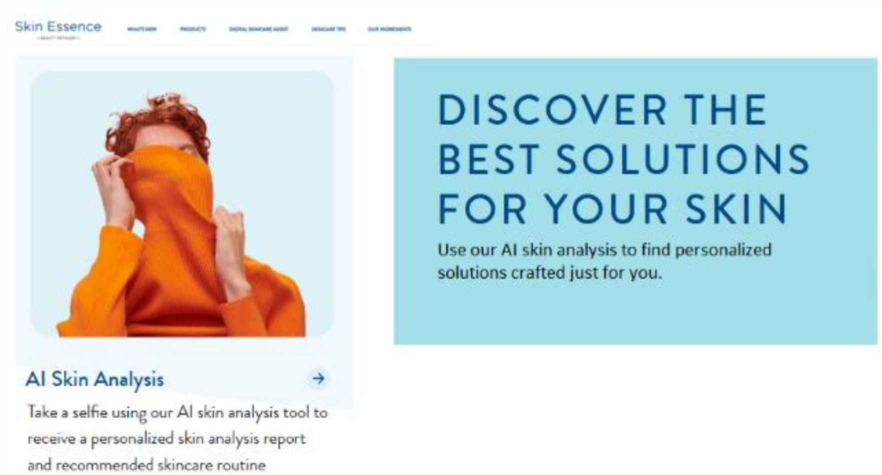
In the following screens, please read the scenario carefully and try to imagine yourself in the described situation as vividly as possible.

You can click next to begin.

------------ Page Break ------------

Imagine that you are looking for a **new** skincare routine and you visit the online store of Skin Essence, a skincare and beauty products retailer.

Upon landing on the main page of Skin Essence, you see the "AI Skin Analysis" tab, a digital shopping assistance tool, which entails taking a selfie for the skin analysis tool to receive a personalized skincare routine recommendation.



You decide to use the "AI Skin Analysis" and clicked on it.

------------ Page Break ------------

On the next page, you are presented with instructions to take the selfie and use the "Skin Essence AI Skin Analysis" tool.

AN AI-POWERED SKIN DIAGNOSIS DEVELOPED WITH DERMATOLOGISTS

GET YOUR MOST ACCURATE SKIN DIAGNOSIS IN 1 MINUTE. TAKE A SELFIE, GET YOUR SKIN ANALYSIS RESULTS AND A PERSONALIZED SKINCARE PROTOCOL.

95% ACCURACY TO DETECT SKIN STRENGTHS

OUR ALGORITHM IS BASED ON 20 YEARS OF SKIN RESEARCH AND TRAINED BY DERMATOLOGIST EVALUATIONS OF OVER 15,000 PHOTOS TO CALCULATE THE SCORE.

TAKE A SELFIE

For a perfect analysis, please follow the following guidelines:

- REMOVE MAKEUP AND GLASSES
- PULL YOUR HAIR BACK
- FACE CAMERA AND KEEP EXPRESSION NEUTRAL
- STAY IN WELL-LIT, NATURAL LIGHT

SKINCONSULT AI needs to access your camera to provide a personalized experience based on your selfie.
Your selfie will not be saved in our database.

TAKE A SELFIE

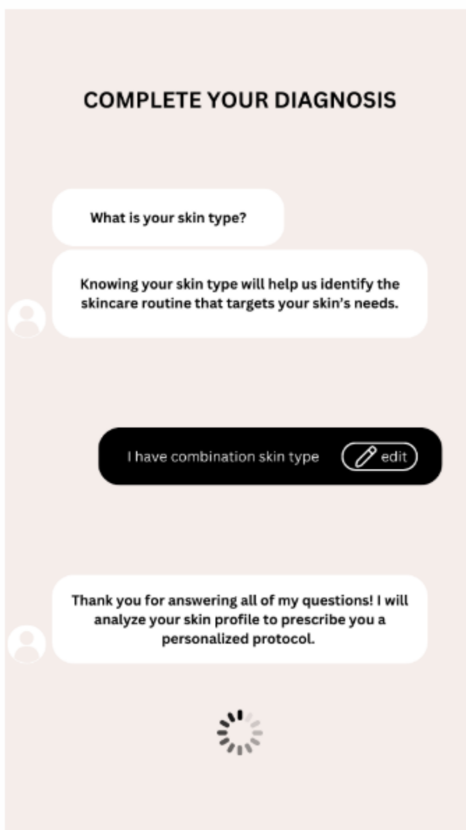
You click on "Take a Selfie".

------------ Page Break ------------

On the following page, you see the interface below to take a selfie for "Skin Essence AI Skin Analysis" tool to develop your skin report:

You take the selfie very easily and submit it for the skin analysis.

Finally, prior to your skin analysis report being developed, you answer a couple of quick questions:

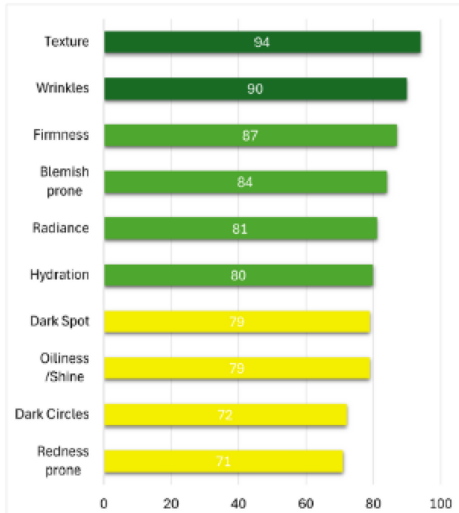


------------ Page Break ------------

Next, you are presented with the skin report from the AI skin analysis based on the selfie that you uploaded:

DISCOVER YOUR COMPLETE SKIN PROFILE

YOUR SKIN HEALTH RATE IS 81



THE SCALE FOR THE SKINCARE REPORT IS AS FOLLOWS:
100 - 90: PERFECT
89 - 80: GOOD
79 - 70: AVERAGE
69 - 50: POOR
49 - 0: VERY POOR

------------ Page Break ------------

[Note: In Experiment 2, participants were asked to complete the perceived control and perceived personalization scales after this page break, prior to receiving product recommendations]

Next, you will receive product recommendations for a skincare routine ***based on the answers you provided to the questions from Product Finder tool***.

Now, please consider the shopping experience you imagined going through until this point and answer the questions below about *how you would feel at this stage of the shopping experience* before you are presented with the product recommendations.

If you were to receive product recommendations for a skincare routine based on the information you provided using the digital shopping assistance tool you imagined using in this shopping experience...

To what extent would you think that the product recommendations for a skincare routine based on the information you provided using the digital shopping assistance tool you used would be...

	Not at all 1	2	3	4	5	6	Very much 7
specially tailored to your needs.	○	○	○	○	○	○	○
more relevant to your preferences or personal needs.	○	○	○	○	○	○	○
the kinds of products that you like.	○	○	○	○	○	○	○
personalized for your unique preferences.	○	○	○	○	○	○	○

Next, you will receive product recommendations for a skincare routine ***based on the answers you provided to the questions from Product Finder tool***.

Now, please consider the shopping experience you imagined going through until this point and answer the questions below about *how you would feel at this stage of the shopping experience* before you are presented with the product recommendations.

If you were to receive product recommendations for a skincare routine based on the information you provided using the digital shopping assistance tool you imagined using in this shopping experience...

------------ Page Break ------------

On the following page, you receive a personalized recommendation for a skincare routine with three products. The recommended skincare routine is based on the skin analysis report from AI Skin Analysis tool:

YOUR PERSONALIZED SKINCARE SOLUTION IS HERE

CLEANSE

Typologie - Exfoliating Cleansing Gel
| 200ml

This gentle micro-exfoliating gel unclogs pores, smooths skin texture, and enhances radiance for a more even complexion. Suitable for all skin types, it transforms into a fine foam when massaged onto damp skin. 98% naturally derived and vegan.

TREAT

Bkind - Soothing Face Serum with Arnica & Hyaluronic Acid
| 48ml

The Soothing Face Serum calms redness and irritation, hydrates, and strengthens the skin barrier with anti-inflammatory and antioxidant ingredients. Its lightweight gel absorbs quickly, leaving skin soothed and ready for moisturizer. Natural, vegan, and recyclable packaging.

MOISTURIZE

Blume - Meltdown Gel Cream with Ceramides
| 50ml

This gel cream hydrates for 72 hours, perfect for all skin types, especially sensitive or acne-prone. With squalane, ceramides, and niacinamide, it plumps, calms, and brightens while protecting against blue light and pollution. Clean, vegan, and cruelty-free.

Imagining yourself in this shopping scenario, please answer the following questions

CLEANSE

Typologie - Exfoliating Cleansing Gel
| 200ml

This gentle micro-exfoliating gel unclogs pores, smooths skin texture, and enhances radiance for a more even complexion. Suitable for all skin types, it transforms into a fine foam when massaged onto damp skin. 98% naturally derived and vegan.

How likely would you be to purchase the recommended product presented above, if you found yourself in this situation?

	1	2	3	4	5	6	7	
Not likely at all	◯	◯	◯	◯	◯	◯	◯	Very likely
Not probable at all	◯	◯	◯	◯	◯	◯	◯	Very probable

TREAT

Bkind - Soothing Face Serum with Arnica & Hyaluronic Acid
| 48ml

The Soothing Face Serum calms redness and irritation, hydrates, and strengthens the skin barrier with anti-inflammatory and antioxidant ingredients. Its lightweight gel absorbs quickly, leaving skin soothed and ready for moisturizer. Natural, vegan, and recyclable packaging.

How likely would you be to purchase the recommended product presented above, if you found yourself in this situation?

	1	2	3	4	5	6	7	
Not likely at all	◯	◯	◯	◯	◯	◯	◯	Very likely
Not probable at all	◯	◯	◯	◯	◯	◯	◯	Very probable

MOISTURIZE

Blume - Meltdown Gel Cream with Ceramides
| 50ml

This gel cream hydrates for 72 hours, perfect for all skin types, especially sensitive or acne-prone. With squalane, ceramides, and niacinamide, it plumps, calms, and brightens while protecting against blue light and pollution. Clean, vegan, and cruelty-free.

How likely would you be to purchase the recommended product presented above, if you found yourself in this situation?

	1	2	3	4	5	6	7	
Not likely at all	○	○	○	○	○	○	○	Very likely
Not probable at all	○	○	○	○	○	○	○	Very probable

Please indicate the extent to which you agree or disagree with the statements below:

I would be...

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
Satisfied with the shopping experience.	○	○	○	○	○	○	○
Pleased with the shopping experience.	○	○	○	○	○	○	○
Happy with the shopping experience.	○	○	○	○	○	○	○

------------ Page Break ------------

Please indicate the extent to which you agree or disagree with the statements below:

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
The shopping experience I imagined going through in this survey could exist in reality as described.	○	○	○	○	○	○	○
The purchase situation I imagined going through on a retailer's website in this survey was realistic.	○	○	○	○	○	○	○
It was very easy for me to put myself into the shopping experience desribed in this survey.	○	○	○	○	○	○	○

Experiment 2: Self-Reported Questionnaire Condition

Shopping Simulation Task

In this study, we kindly invite you to go through a shopping simulation, which requires you to imagine yourself in the scenario described in the following pages and answer the questions that follow.

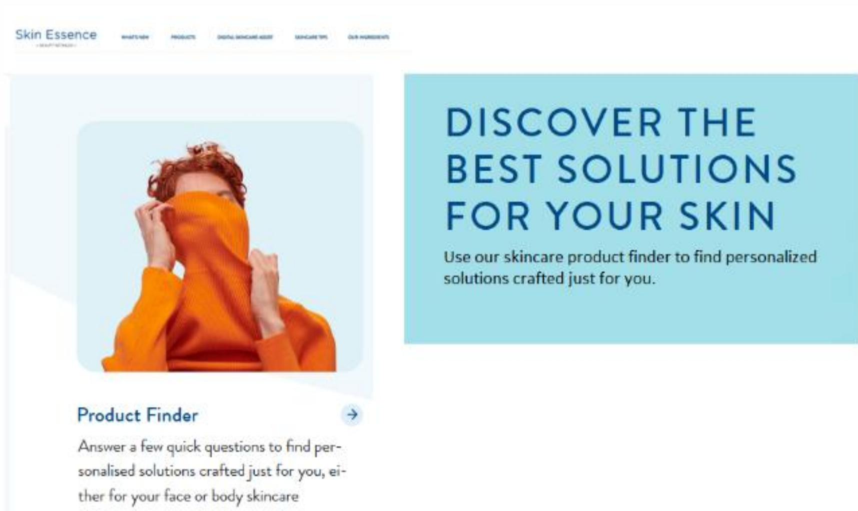
In the following screens, please read the scenario carefully and try to imagine yourself in the described situation as vividly as possible.

You can click next to begin.

------------ Page Break ------------

Imagine that you are looking for a **new** skincare routine and you visit the online store of Skin Essence, a skincare and beauty products retailer.

Upon landing on the main page of Skin Essence, you see the "Product Finder" tab, a digital shopping assistance tool, which entails answering a series of questions to receive a personalized skincare routine recommendation.



You decided to use the "Product Finder" tool and clicked on it.

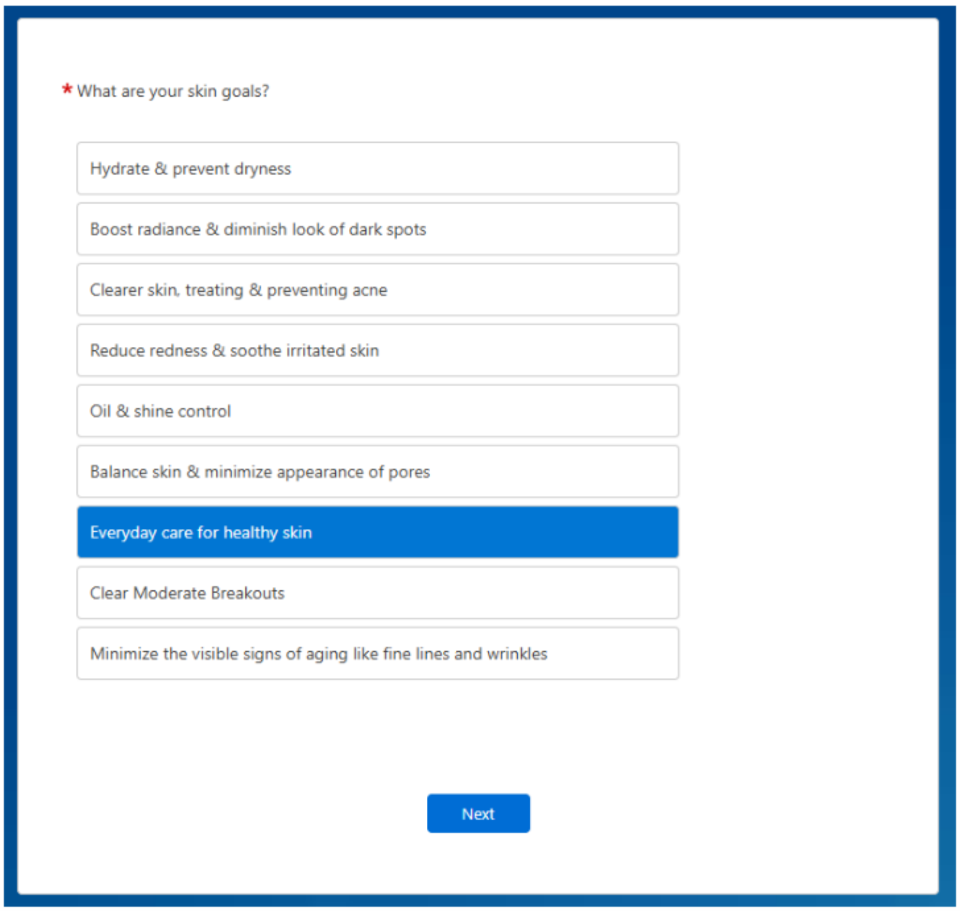
------------ Page Break ------------

The "Product Finder" tool then asks you to answer a series of questions.

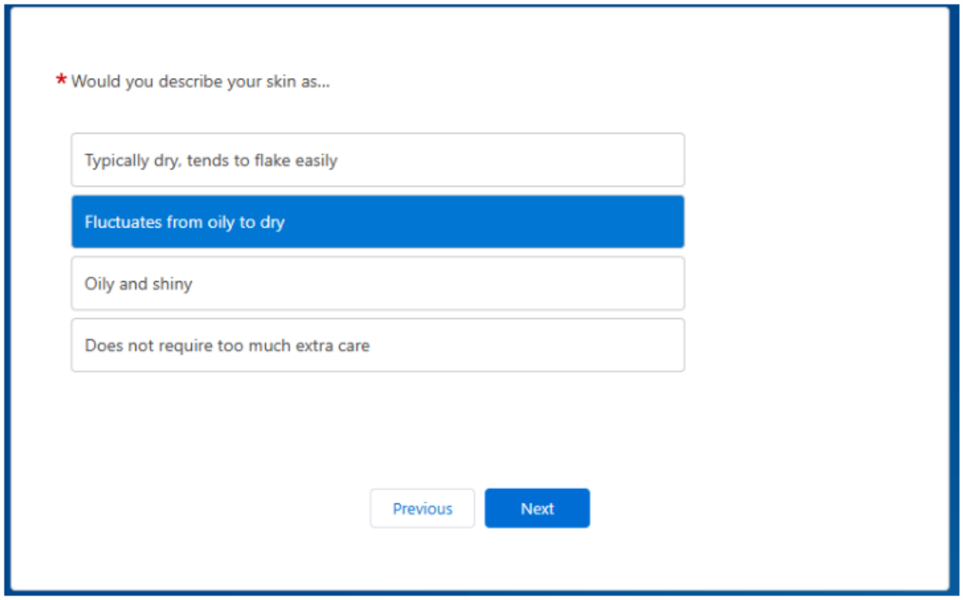
You answer the questions one by one and click next after answering each question.

Please see the questions and your answer to each question:

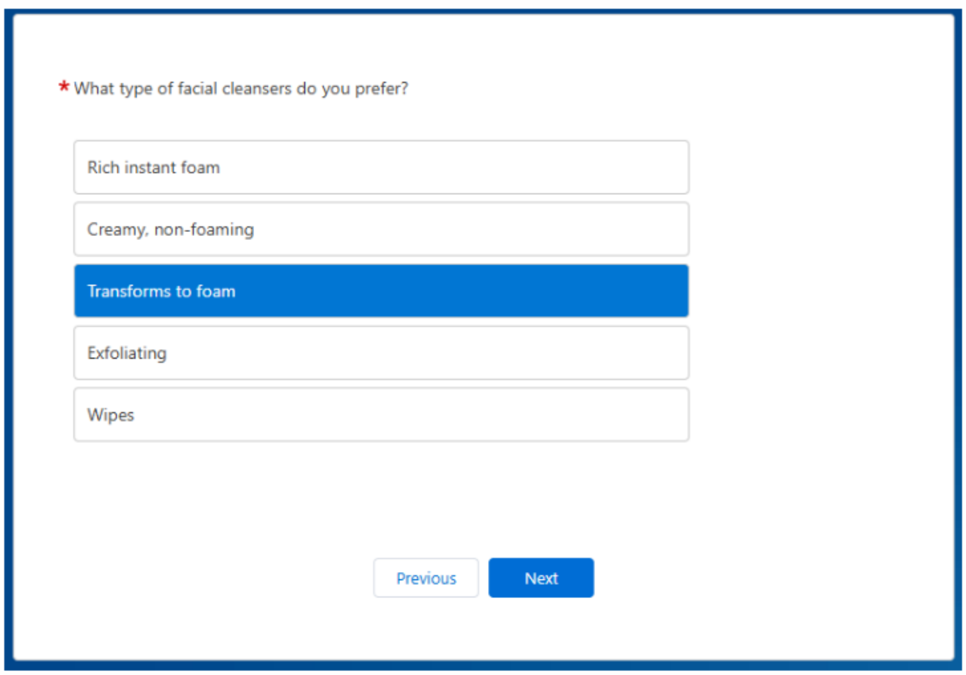
Question 1



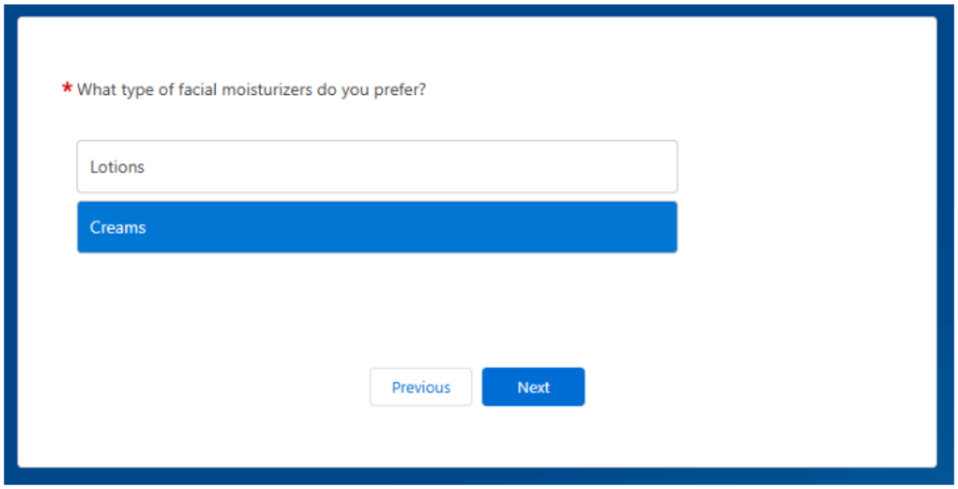
Question 2



Question 3



Question 4

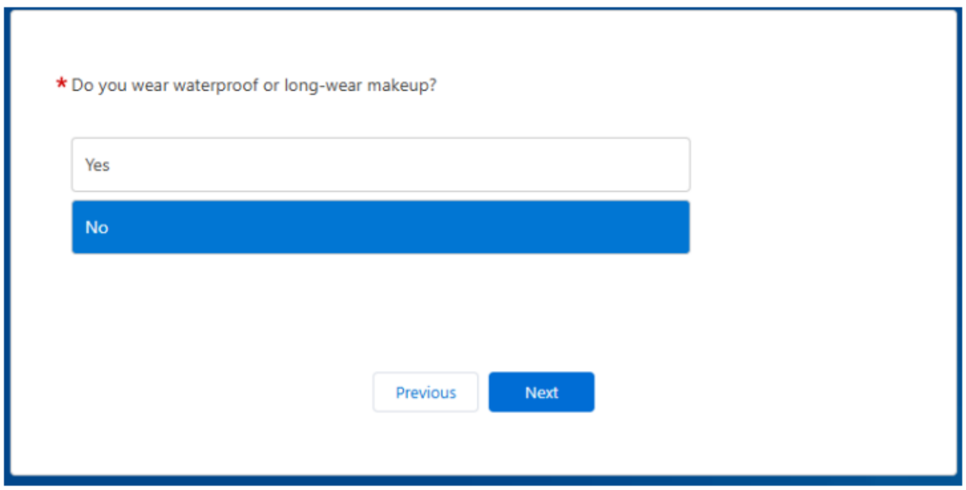

* What type of facial moisturizers do you prefer?

Lotions

Creams

Previous Next

Question 5

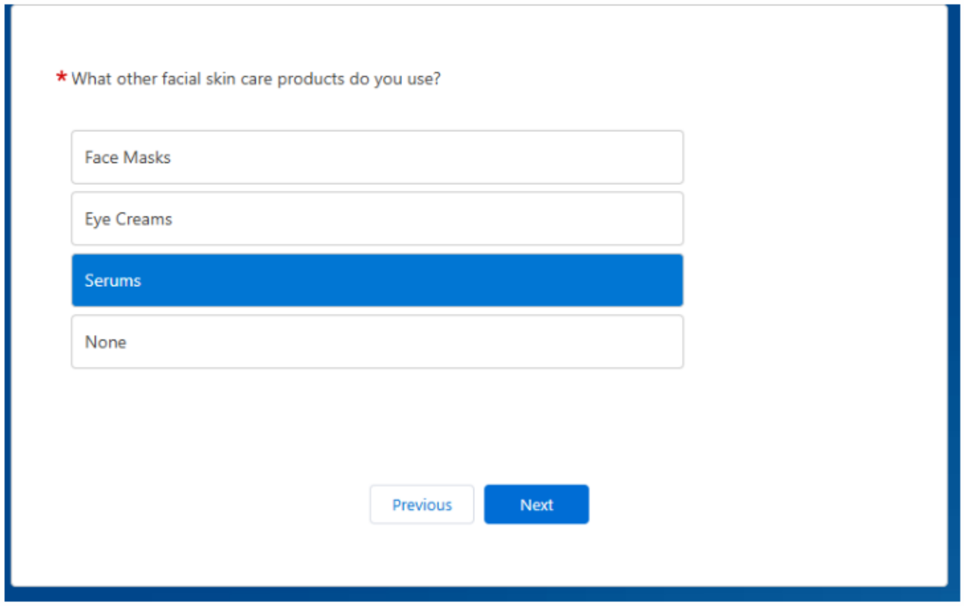

* Do you wear waterproof or long-wear makeup?

Yes

No

Previous Next

Question 6



Question 7 (The Last Question)

You answer the last question as "Somewhat sensitive" and clicks on "Finish".

------------ Page Break ------------

[Note: In Experiment 2, participants were asked to complete the perceived control and perceived personalization scales after this page break, prior to receiving product recommendations]

Next, you will receive product recommendations for a skincare routine ***based on the answers you provided to the questions from Product Finder tool***.

Now, please consider the shopping experience you imagined going through until this point and answer the questions below about *how you would feel at this stage of the shopping experience* before you are presented with the product recommendations.

If you were to receive product recommendations for a skincare routine based on the information you provided using the digital shopping assistance tool you imagined using in this shopping experience...

To what extent would you think that the product recommendations for a skincare routine based on the information you provided using the digital shopping assistance tool you used would be...

	Not at all 1	2	3	4	5	6	Very much 7
specially tailored to your needs.	○	○	○	○	○	○	○
more relevant to your preferences or personal needs.	○	○	○	○	○	○	○
the kinds of products that you like.	○	○	○	○	○	○	○
personalized for your unique preferences.	○	○	○	○	○	○	○

Next, you will receive product recommendations for a skincare routine ***based on the answers you provided to the questions from Product Finder tool***.

Now, please consider the shopping experience you imagined going through until this point and answer the questions below about *how you would feel at this stage of the shopping experience* before you are presented with the product recommendations.

If you were to receive product recommendations for a skincare routine based on the information you provided using the digital shopping assistance tool you imagined using in this shopping experience...

------------ Page Break ------------

On the following page, you receive a personalized recommendation for a skincare routine with three products. The recommended skincare routine is based on the answers you provided to the questions from Product Finder tool:

YOUR PERSONALIZED SKINCARE SOLUTION IS HERE

CLEANSE

Typologie - Exfoliating Cleansing Gel
| 200ml

This gentle micro-exfoliating gel unclogs pores, smooths skin texture, and enhances radiance for a more even complexion. Suitable for all skin types, it transforms into a fine foam when massaged onto damp skin. 98% naturally derived and vegan.

TREAT

Bkind - Soothing Face Serum with Arnica & Hyaluronic Acid
| 48ml

The Soothing Face Serum calms redness and irritation, hydrates, and strengthens the skin barrier with anti-inflammatory and antioxidant ingredients. Its lightweight gel absorbs quickly, leaving skin soothed and ready for moisturizer. Natural, vegan, and recyclable packaging.

MOISTURIZE

Blume - Meltdown Gel Cream with Ceramides
| 50ml

This gel cream hydrates for 72 hours, perfect for all skin types, especially sensitive or acne-prone. With squalane, ceramides, and niacinamide, it plumps, calms, and brightens while protecting against blue light and pollution. Clean, vegan, and cruelty-free.

Imagining yourself in this shopping scenario, please answer the following questions

CLEANSE

Typologie - Exfoliating Cleansing Gel
| 200ml

This gentle micro-exfoliating gel unclogs pores, smooths skin texture, and enhances radiance for a more even complexion. Suitable for all skin types, it transforms into a fine foam when massaged onto damp skin. 98% naturally derived and vegan.

How likely would you be to purchase the recommended product presented above, if you found yourself in this situation?

	1	2	3	4	5	6	7	
Not likely at all	○	○	○	○	○	○	○	Very likely
Not probable at all	○	○	○	○	○	○	○	Very probable

TREAT

Bkind - Soothing Face Serum with Arnica & Hyaluronic Acid
| 48ml

The Soothing Face Serum calms redness and irritation, hydrates, and strengthens the skin barrier with anti-inflammatory and antioxidant ingredients. Its lightweight gel absorbs quickly, leaving skin soothed and ready for moisturizer. Natural, vegan, and recyclable packaging.

How likely would you be to purchase the recommended product presented above, if you found yourself in this situation?

	1	2	3	4	5	6	7	
Not likely at all	○	○	○	○	○	○	○	Very likely
Not probable at all	○	○	○	○	○	○	○	Very probable

MOISTURIZE

Blume - Meltdown Gel Cream with Ceramides
| 50ml

This gel cream hydrates for 72 hours, perfect for all skin types, especially sensitive or acne-prone. With squalane, ceramides, and niacinamide, it plumps, calms, and brightens while protecting against blue light and pollution. Clean, vegan, and cruelty-free.

How likely would you be to purchase the recommended product presented above, if you found yourself in this situation?

	1	2	3	4	5	6	7	
Not likely at all	○	○	○	○	○	○	○	Very likely
Not probable at all	○	○	○	○	○	○	○	Very probable

Please indicate the extent to which you agree or disagree with the statements below:

I would be...

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
Satisfied with the shopping experience.	○	○	○	○	○	○	○
Pleased with the shopping experience.	○	○	○	○	○	○	○
Happy with the shopping experience.	○	○	○	○	○	○	○

------------ Page Break ------------

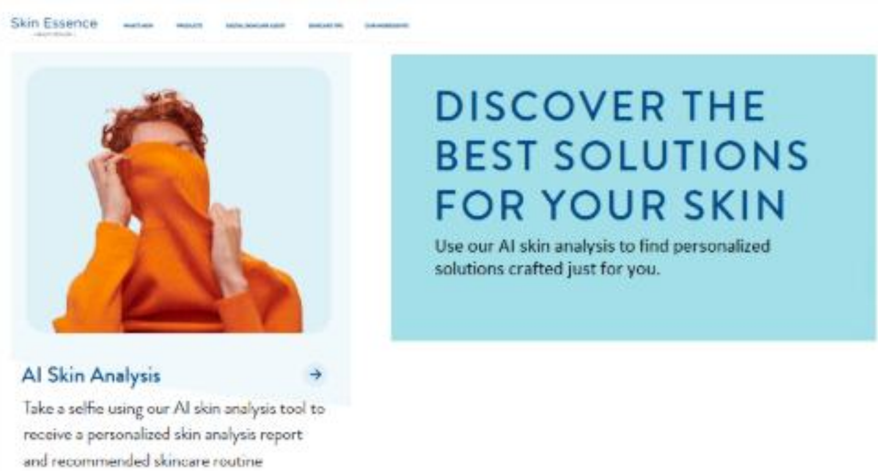
Please indicate the extent to which you agree or disagree with the statements below:

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
The shopping experience I imagined going through in this survey could exist in reality as described.	○	○	○	○	○	○	○
The purchase situation I imagined going through on a retailer's website in this survey was realistic.	○	○	○	○	○	○	○
It was very easy for me to put myself into the shopping experience desribed in this survey.	○	○	○	○	○	○	○

Experiment 3: AI Diagnostic Tool – Measurement Task Present Condition[6]

Imagine that <u>you are looking for a **new** skincare routine</u> and you visit the online store of Skin Essence, a skincare and beauty products retailer.

Upon landing on the main page of Skin Essence, you see the "AI Skin Analysis" tab, a <u>digital shopping assistance tool</u>, which entails answering a few questions and taking a selfie for the skin analysis tool to provide a personalized skincare routine recommendation.



You decide to use the "AI Skin Analysis" and clicked on it.

------------ Page Break ------------

[6] AI Diagnostic Tool – Measurement Task Absent and Self-Reported Questionnaire – Measurement Task Absent conditions were identical to the conditions in Experiment 2.

On the next page, you are presented with instructions on how to use the "Skin Essence AI Skin Analysis" tool.

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OUR ALGORITHM IS BASED ON 20 YEARS OF SKIN RESEARCH AND TRAINED BY DERMATOLOGIST EVALUATIONS OF OVER 15,000 PHOTOS TO CALCULATE THE SCORE.

------------ Page Break ------------

First, you are asked to answer a couple of quick questions about yourself and your environment. You answer the questions one by one and click next after answering each question.

Please see the questions and your answer to each question:

Question 1

*Where do you live? *Different environments impact skin differently, such as pollution, humidity, or dry air.*

- City
- Suburban
- Countryside

Next

Question 2

*What is the weather like in your area most of the time? *Sun exposure affects skin aging, hydration, and pigmentation.*

- Mostly sunny
- Mostly cloudy
- A mix of both

Previous Next

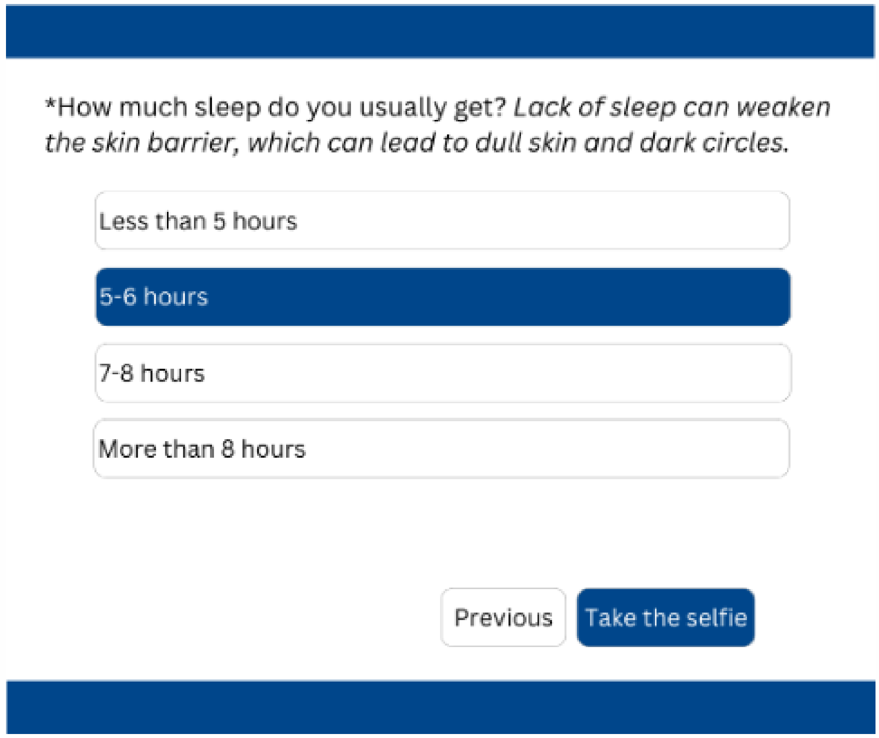
Question 3

*Do you often feel stressed or tense? *Stress increases cortisol and adrenaline, which can lead to inflammation, acne, eczema, and other skin issues.*

- Yes, everyday
- Often
- Rarely
- Never

Previous | Next

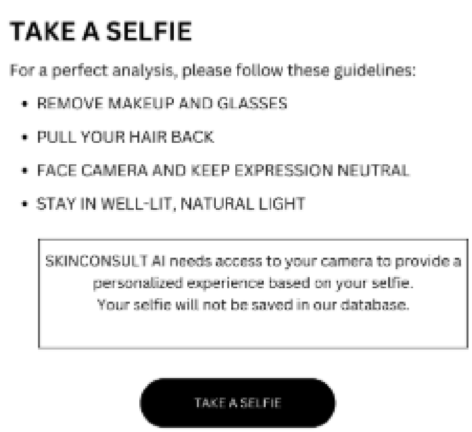
Question 4 (The Last Question)



You answer the last question as "5-6 hours" and click on "Take the selfie".

------------ Page Break ------------

On the next page, you are presented with instructions on how to take the selfie.



You click on "Take the selfie".

------------ Page Break ------------

On the following page, you see the interface below to take a selfie for "Skin Essence AI Skin Analysis" tool to develop your skin report:

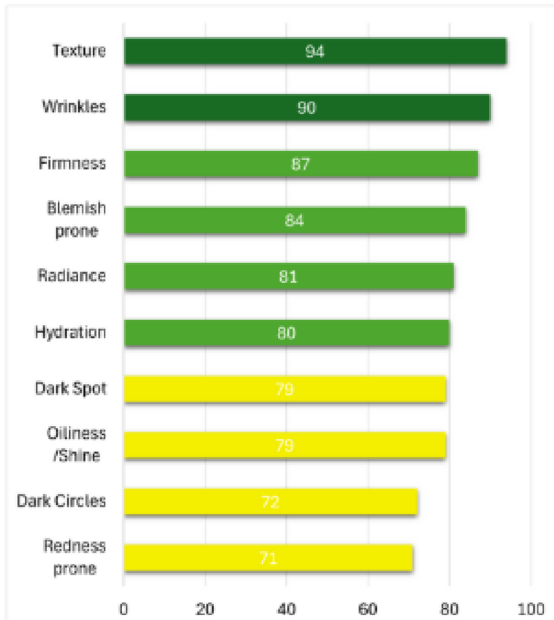
You take the selfie very easily and submit it for the skin analysis.

------------ Page Break ------------

Next, you are presented with the skin report from the AI skin analysis based on the selfie that you uploaded and the questions you previously answered:

DISCOVER YOUR COMPLETE SKIN PROFILE

YOUR SKIN HEALTH RATE IS 81



THE SCALE FOR THE SKINCARE REPORT IS AS FOLLOWS:
100 - 90: PERFECT
89 - 80: GOOD
79 - 70: AVERAGE
69 - 50: POOR
49 - 0: VERY POOR

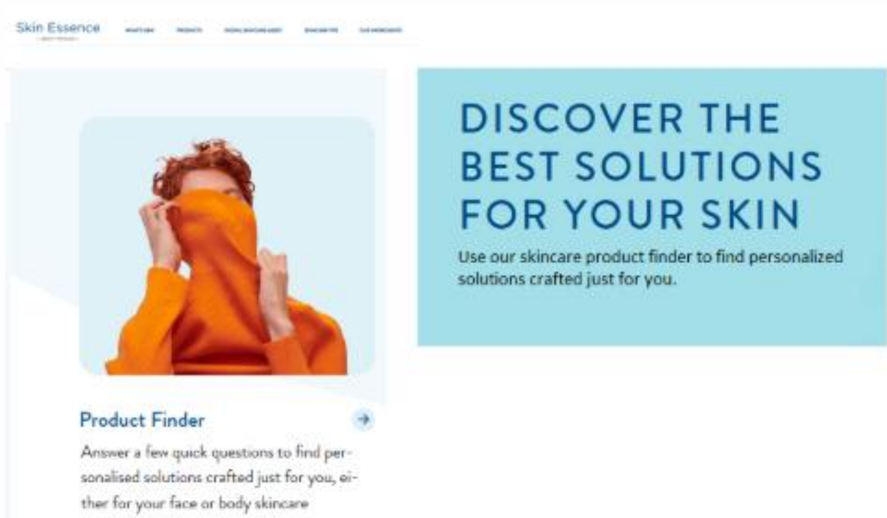
------------ Page Break[7] ------------

[7] Following this page, the participants responded to perceived personalization and perceived control scales, were presented with the product recommendations, indicated their purchase intentions for each product, and indicated their satisfaction with the shopping experience as in Experiment 2.

Experiment 3: Self-Reported Questionnaire – Measurement Task Present Condition

Imagine that you are looking for a **new** skincare routine and you visit the online store of Skin Essence, a skincare and beauty products retailer.

Upon landing on the main page of Skin Essence, you see the "Product Finder" tab, a digital shopping assistance tool, which entails answering a series of questions to receive a personalized skincare routine recommendation.



You decided to use the "Product Finder" tool and clicked on it.

------------ Page Break ------------

The "Product Finder" tool then asks you to answer a series of questions.

You answer the questions one by one and click next after answering each question.

Please see the questions and your answer to each question:

Question 1

*What are your skin goals?

- Hydrate & prevent dryness
- Boost radiance & diminish look of dark spots
- Clearer skin, treating & preventing acne
- Reduce redness & soothe irritated skin
- Oil & shine control
- Balance skin & minimize appearance of pores
- Everyday care for healthy skin
- Clear moderate breakouts
- Minimize the visible signs of aging like fine lines and wrinkles

Next

Question 2

*Would you describe your skin as...

- Typically dry, tends to flake easily
- Fluctuates from oily to dry
- Oily and shiny
- Does not require too much extra care

Previous Next

Question 3

*What type of facial cleanser do you prefer?

- Rich instant foam
- Creamy, non-foaming
- Transforms to foam
- Exfoliating
- Wipes

Previous Next

Question 4

*What type of facial moisturizers do you prefer?

Lotions

Creams

Previous Next

Question 5

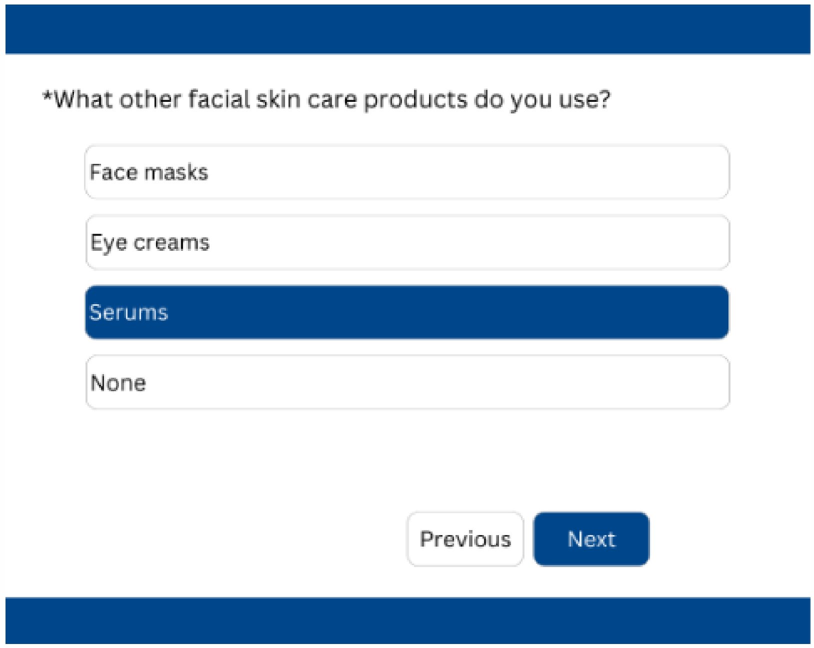
*Do you wear waterproof or long-wear makeup?

Yes

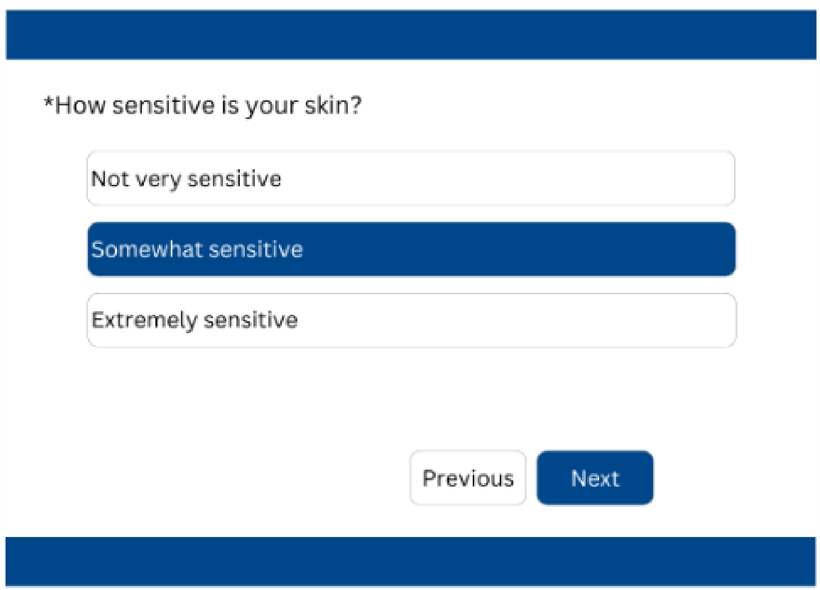
No

Previous Next

Question 6



Question 7



Question 8

*Where do you live? *Different environments impact skin differently, such as pollution, humidity, or dry air.*

- City
- Suburban
- Countryside

Previous | Next

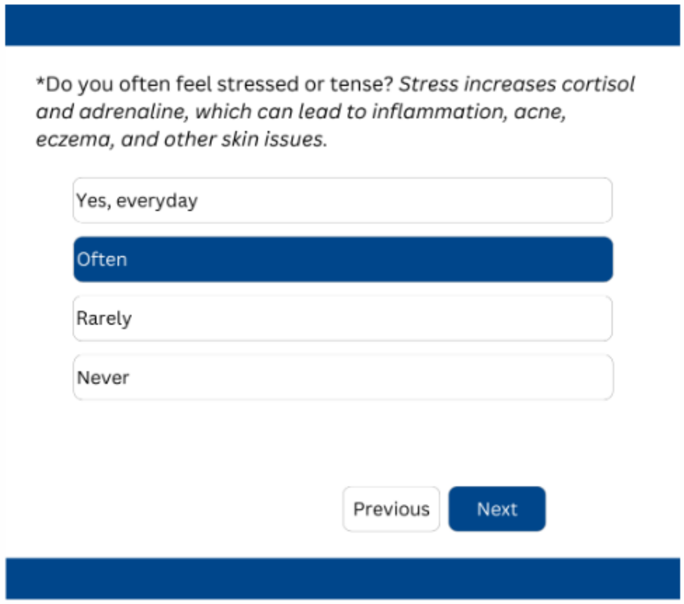
Question 9

*What is the weather like in your area most of the time? *Sun exposure affects skin aging, hydration, and pigmentation.*

- Mostly sunny
- Mostly cloudy
- A mix of both

Previous | Next

Question 10



*Do you often feel stressed or tense? *Stress increases cortisol and adrenaline, which can lead to inflammation, acne, eczema, and other skin issues.*

Yes, everyday

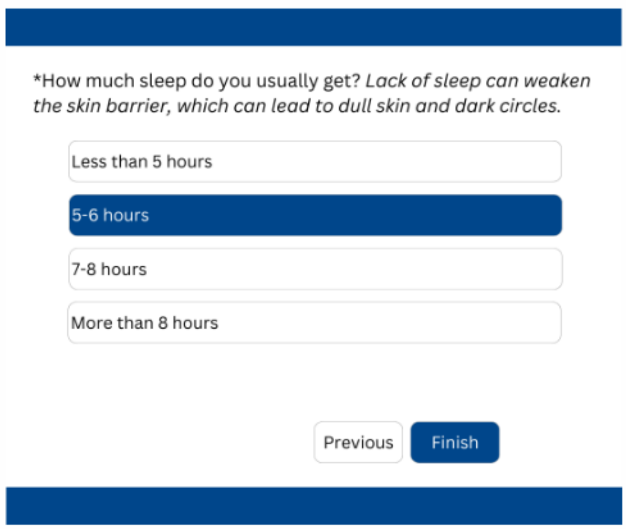
Often

Rarely

Never

Previous Next

Question 11 (The Last Question)



*How much sleep do you usually get? *Lack of sleep can weaken the skin barrier, which can lead to dull skin and dark circles.*

Less than 5 hours

5-6 hours

7-8 hours

More than 8 hours

Previous Finish

You answer the last question as "5-6 hours" and click on "Finish".

------------ Page Break[8] ------------

[8] Following this page, the participants responded to perceived personalization and perceived control scales, were presented with the product recommendations, indicated their purchase intentions for each product, and indicated their satisfaction with the shopping experience as in Experiment 2.

Appendix B: Measurement Scales Used in Experiments

Variables	Items[9]	Cronbach's Alpha			Source
		Exp. 1	Exp. 2	Exp. 3	
Purchase Intentions[10]	How likely would you be to purchase the recommended product presented above, if you found yourself in this situation? [*Not likely at all / Very likely*] [*Not probable at all / Very probable*]	.964 .962 .977	.977 .974 .988	.971 .968 .957	Items adapted from the "Willingness to Purchase" scale, Zúñiga (2016)
Satisfaction	I would be satisfied with the shopping experience. I would be happy with the shopping experience. I would be pleased with the shopping experience.	.966	.975	.976	Items adapted from the "Satisfaction with the Salespeople's Service" scale, Wang et al. (2018)
Realism	The shopping experience I imagined going through in this survey could exist in reality as described. The purchase situation I imagined going through on a retailer's website in this survey was realistic. It was very easy for me to put myself into the shopping experience described in this survey.	.907	.883	.883	Items adapted from the "Realism of the Purchase Simulation" scale, Emrich et al. (2015)
Perceived Personalization[11]	Specially tailored to your needs. More relevant to your preferences or personal needs. The kinds of products that you like. Personalized for your unique preferences.	-	.926	.918	Items adapted from the "Customizability" scale, Wang et al. (2024).
Perceived Control	I would feel like I had control over how the product recommendations that I would receive are generated.	-	.945	.920	Items adapted from "Perceived Control" scales, Hu & Wise, (2021); Degachi et

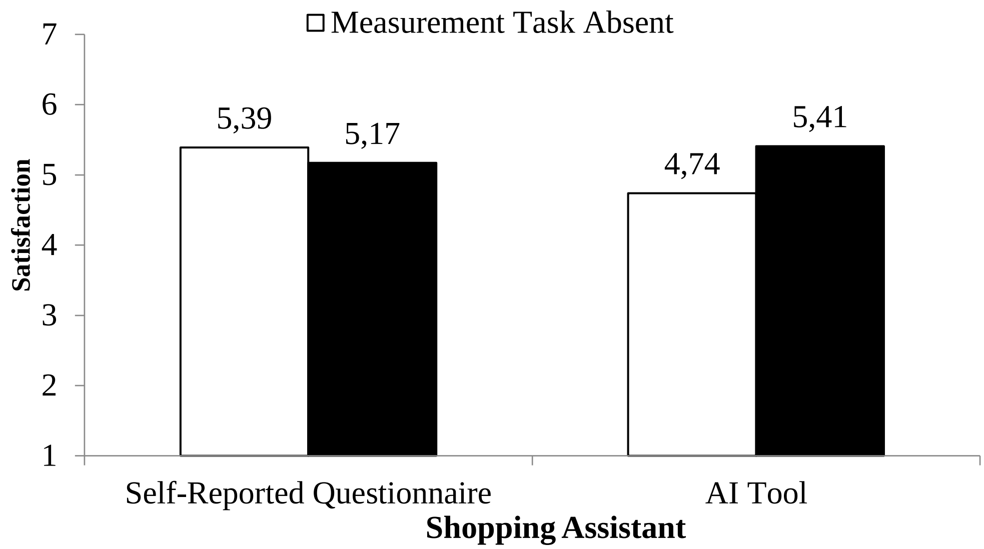
[9] Scales: 7-point Likert scale *(1 = Not at all / 7 = Very much)* for all variables but purchase intentions.
[10] For purchase intentions, Cronbach's alpha was calculated separately for each product across all three studies.
[11] Full item wording: To what extent would you think that the product recommendations for a skincare routine based on the information you provided using the digital shopping assistance tool you used would be…

	I would feel like my input would have a strong influence on the product recommendations that I would receive. I would feel like I had an influence on the generation of the product recommendations that I would receive. I would feel like I was able to clearly communicate my preferences for the product recommendations that I would receive.	al. (2023); Rohden & Espartel (2024).

Appendix C: Experiment 3 – Results for Satisfaction with the Shopping Experience

Satisfaction. In this section, we examine whether the presence of a measurement task mitigates the negative effect of the AI diagnostic tool on satisfaction with the shopping experience (vs. self-reported questionnaire). Since lower levels of perceived personalization are associated with lower satisfaction outcomes (Franke et al., 2009; Dabholkar & Sheng, 2012), we predict that adding a measurement task (i.e., contextual questions) will enhance participants' sense of uniqueness acknowledgment, thereby increasing perceived personalization and, in turn, improving satisfaction (Kramer, 2007). Therefore, when the measurement task is absent, we expect participants using the AI tool (vs. self-reported questionnaire) to report lower satisfaction. However, this negative effect should disappear when the measurement task is present. We anticipate that this effect will be stronger in the AI tool condition, where user involvement is limited, than in the self-reported questionnaire condition, which already incorporates direct consumer input. To test these predictions, we conducted an ANOVA with shopping assistant (self-reported questionnaire = –1, AI tool = 1) and measurement task (absent = –1 vs. present = 1) as independent variables and satisfaction as the dependent variable. The analysis revealed only a significant interaction between shopping assistant and measurement task ($F(1, 131) = 4.20$, $p = .043$, $\eta^2 = .031$). When the measurement task was absent, participants in the AI tool condition reported significantly lower satisfaction than those in the self-reported questionnaire condition ($M_{\text{AI tool}} = 4.73$, $SD = 1.68$ vs. $M_{\text{self-reported questionnaire}} = 5.39$, $SD = 1.00$; $F(1, 131) = 4.70$, $p = .032$, $\eta^2 = .035$). When the measurement task was present, there were no significant differences between the two conditions ($M_{\text{AI tool}} = 5.41$, $SD = 1.03$ vs. $M_{\text{self-reported questionnaire}} = 5.17$, $SD = 1.27$; $F(1, 131) = .57$, $p > .40$, $\eta^2 = .004$). Moreover, in the AI tool condition, satisfaction was significantly lower when contextual questions were absent than when present ($M_{\text{absent}} = 4.73$, $SD = 1.68$ vs. $M_{\text{present}} = 5.41$, $SD = 1.03$; $F(1, 131) = 4.54$, $p = .035$, $\eta^2 = .034$). In contrast, in the self-reported questionnaire condition, there were no significant differences between the absence and presence ($M_{\text{absent}} = 5.39$, $SD = 1.00$ vs. $M_{\text{present}} = 5.17$, $SD = 1.27$) of contextual questions ($F(1, 131) = .52$, $p > .40$, $\eta^2 = .004$). This interaction is illustrated in Figure 4, and the results support our predictions outlined in H_{4b}.

Figure 4 – The Effect of Shopping Assistant on Satisfaction as a Function of Measurement Task, Experiment 2



Next, we conducted a moderated mediation analysis using PROCESS Model 8 (Hayes, 2018) with 5,000 bootstrap samples, in which shopping assistant (self-reported questionnaire = –1, AI = 1) was entered as the independent variable, perceived personalization as the mediator, measurement task (absent = –1 vs. present = 1) as the moderator, and satisfaction as the dependent variable. The model tested whether the indirect effect of shopping assistant on satisfaction through perceived personalization depended on the inclusion of a measurement task. When the measurement task was absent, the indirect effect of shopping assistant on satisfaction, controlling for perceived personalization, was significant ($b_{indirect}$ = –.30, *SE* = .12, 95% *CI* [–.53; –.08]), while the direct effect disappeared (*b* = –.03, *SE* = .12, 95% *CI* [–.28; .21]). When the measurement task was present, the indirect effect of shopping assistant on satisfaction through perceived personalization disappeared ($b_{indirect}$ = –.02, *SE* = .08, 95% *CI* [–.17; .16]). Lastly, we obtained a statistically significant index of moderated mediation through perceived personalization (b_{index} = .28, *SE* = .15, 95% *CI* = [.01; .59]). This result supports our prediction that the measurement task moderates the impact of the shopping assistant on satisfaction primarily through perceived personalization.

Finally, we conducted a moderated parallel mediation analysis using PROCESS (model 8, 5,000 bootstrap samples, Hayes 2018) with shopping assistant (self-reported questionnaire = –1, AI = 1) as the independent variable, perceived control and perceived personalization as parallel mediators, measurement task (absent = –1 vs. present = 1) as the moderator, and satisfaction as the dependent variable. This model tested whether the indirect effect of shopping assistant on satisfaction through perceived control and perceived personalization depended on the inclusion of a measurement task. When the measurement task was absent, the indirect effect of shopping assistant on satisfaction was significant through both perceived control (b_{indirect} = –.20, *SE* = .08, 95% *CI* [–.38; –.07]) and perceived personalization (b_{indirect} = –.17, *SE* = .08, 95% *CI* [–.34; –.04]), while the direct effect disappeared (*b* = .04, *SE* = .11, 95% *CI* [–.19; .26]). When the contextual cues were present, the indirect effect of shopping assistant through perceived control was significant (b_{indirect} = –.13, *SE* = .07, 95% *CI* [–.274; –.002]), while the indirect effect through perceived personalization disappeared (b_{indirect} = –.01, *SE* = .05, 95% *CI* [–.11; .09]). Importantly, in line with our previous experiment, we obtained a statistically significant index of moderated mediation through perceived personalization (b_{index} = .16, *SE* = .09, 95% *CI* [.004; .376]), but not through perceived control (b_{index} = .07, *SE* = .10, 95% *CI* = [–.10; .29]), suggesting that the moderating role of measurement task is specific to perceived personalization. However, the direct effect of shopping assistant on satisfaction was significant when the measurement task was present (*b* = .26, *SE* = .12, 95% *CI* [.03; .49]). These findings further reinforce the central role of perceived personalization in shaping satisfaction. However, satisfaction may also be enhanced through additional unmeasured mechanisms.

Appendix D: AI Declaration of Use

Artificial Intelligence (AI) tools were utilized throughout this thesis as supportive instruments in the following areas:

- Translation
- Reformulation and rephrasing
- Proofreading and language corrections
- Clarification of ideas

AI was employed only as an aid to improve the writing process, especially to enhance the clarity, coherence and linguistic quality of the text, as well as to facilitate translation tasks. All AI-generated suggestions were thoroughly reviewed, adapted, and, when necessary, corrected by me before being integrated into the thesis, to ensure that the underlying structure, original ideas and personal writing style remained entirely my own. All ideas, interpretations, analyses, and conclusions in this thesis are the result of my own critical thinking and personal reasoning. AI tools were used solely for linguistic support without contributing to the intellectual substance of the work.

Tools References

OpenAI. (2025). *ChatGPT* (Version 4.0) [Large language model used for translation, language improvement, clarification, and proofreading].

DeepL. (2025). *DeepL Translator* [Translation software].

Appendix E: Research Certificates of Ethics Approval

HEC MONTRÉAL

Comité d'éthique de la recherche

CERTIFICATE OF ETHICS APPROVAL

This is to confirm that the research project described below has been evaluated in accordance with ethical conduct for research involving human subjects, and that it meets the requirements of our policy on that subject.

Project No.: 2025-6254

Title of research project: Investigating the influence of AI tools versus human agents in skincare diagnosis and recommendations on consumer experience.

Principal investigator: Romane Cabart

Date of project approval: December 13, 2024
Effective date of certificate: December 13, 2024
Expiry date of certificate: December 01, 2025

Maurice Lemelin
Président
CER de HEC Montréal

Signé le 2024-12-13 à 14:52

NAGANO Approval of project further to conditional approval
Comité d'éthique de la recherche - HEC Montréal 2 / 2

HEC MONTRĒAL

Comité d'éthique de la recherche

ATTESTATION D'APPROBATION ÉTHIQUE COMPLÉTÉE

La présente atteste que le projet de recherche décrit ci-dessous a fait l'objet des approbations en matière d'éthique de la recherche avec des êtres humains nécessaires selon les exigences de HEC Montréal.

La période de validité du certificat d'approbation éthique émis pour ce projet est maintenant terminée. Si vous devez reprendre contact avec les participants ou reprendre une collecte de données pour ce projet, la certification éthique doit être réactivée préalablement. Vous devez alors prendre contact avec le secrétariat du CER de HEC Montréal.

Projet # : 2025-6254 - AI Tools

Titre du projet de recherche : Investigating the Influence of AI Tools Versus Human Agents on Consumer Experience in Skincare Diagnosis and Product Recommendations

Chercheur principal : Romane Cabart

Directeur/codirecteurs : Ali Tezer

Date d'approbation initiale du projet : December 13, 2024

Date de fermeture de l'approbation éthique : April 14, 2025

Maurice Lemelin
Président
CER de HEC Montréal

Signé le 2025-04-15 à 13:29