INSTITUTO
UNIVERSITÁRIO
DE LISBOA

# AI-Driven Personalization in Fast Fashion and its Implications for Consumer Behavior and Sustainability

Joana Arruda André

Master in Marketing

Supervisor:
Doctor Sandra Maria Correia Loureiro, Full Professor at ISCTE-IUL Business School, Department of Marketing, Operations and General Management, ISCTE Instituto Universitário de Lisboa

July, 2024

BUSINESS
SCHOOL

Department of Marketing, Operations and General Management

# AI-Driven Personalization in Fast Fashion and its Implications for Consumer Behavior and Sustainability

Joana Arruda André

Master in Marketing

Supervisor:
Doctor Sandra Maria Correia Loureiro, Full Professor at ISCTE-IUL Business School, Department of Marketing, Operations and General Management, ISCTE Instituto Universitário de Lisboa

July, 2024

## Acknowledgments

Firstly, I extend my deepest gratitude to my supervisor, Professor Sandra Loureiro, for her invaluable guidance, steadfast support, and dedication throughout this process. Her expertise, flexibility in communication, and provision of insightful materials and reputable references have significantly enriched the quality of my work. Her adeptness in aligning discussion topics with my research interests has been instrumental in shaping the trajectory of my study.

I am also grateful to my closest peers for their companionship during numerous hours spent in the library and beyond, engaging in stimulating discussions related to marketing, fashion, and technology, and for sharing the joys and struggles during this period. Their diverse perspectives have broadened my understanding and enriched my research endeavors.

Besides, I would like to extend my appreciation to the ISCTE Business School members who facilitated connections with knowledgeable academics, providing invaluable assistance during moments of uncertainty. Additionally, I am grateful to my professors for equipping me with valuable tools, tips, and knowledge throughout this master's program.

To my beloved family and friends, your unwavering encouragement and support have been my anchor throughout this journey. Special thanks to my parents, grandparents, and uncles for their constant advocacy for my well-being and intellectual growth. Your belief in my abilities and resilience has been a source of inspiration, propelling me forward during challenging times.

Lastly, I acknowledge the personal dedication and perseverance that were crucial in completing this dissertation. The countless hours of hard work and determination have been a significant part of this course, and I am grateful for the strength to see it through to the end.

**Abstract**

This dissertation delves into the profound impact of AI-driven personalization on consumer behavior and sustainability within the fast fashion industry. Through a comprehensive examination of the complex intersections among technological innovation, consumer preferences, privacy considerations, and ethical imperatives, the study offers valuable insights into the contemporary dynamics of fast fashion marketing. The research reveals that AI-driven personalization significantly influences consumer purchase behavior, enhancing engagement and increasing purchase intentions, albeit moderated by privacy concerns and ethical considerations. Moreover, emerging trends and technological advancements, particularly in AI, reshape consumer engagement and market dynamics, emphasizing the need for continuous adaptation and innovation by industry stakeholders. The critical role of sustainable practices and ethical initiatives in mitigating the environmental footprint of fast fashion is underscored, with consumers increasingly valuing sustainability and ethical commitments. Drawing from these findings, the study provides recommendations for fast fashion brands to prioritize transparency, leverage AI technologies for sustainable product development, continuously innovate, and integrate ethical considerations into AI implementation.

**Keywords:** Artificial Intelligence (AI), Fast Fashion industry, AI-driven personalization, Sustainability, Consumer engagement, Well-being

JEL: M31 – Marketing

JEL: M39 – Marketing and Advertising: Other

## Resumo

Esta dissertação explora a profunda influência da personalização impulsionada por IA no comportamento do consumidor e na sustentabilidade dentro da indústria da moda rápida. Através de uma análise abrangente das complexas interseções entre inovação tecnológica, preferências do consumidor, considerações de privacidade e imperativos éticos, o estudo oferece perceções valiosas sobre a dinâmica contemporânea do marketing de moda rápida. A pesquisa revela que a personalização impulsionada por IA influencia significativamente o comportamento de compra do consumidor, melhorando o compromisso e aumentando as intenções de compra, embora moderadas por preocupações de privacidade e considerações éticas. Além disso, tendências emergentes e avanços tecnológicos, particularmente em IA, remodelam o compromisso do consumidor e a dinâmica de mercado, enfatizando a necessidade de adaptação e inovação contínuas por parte dos stakeholders da indústria. O papel crítico das práticas sustentáveis e iniciativas éticas na mitigação do efeito ambiental da moda rápida é sublinhado, com os consumidores valorizando cada vez mais a sustentabilidade e os comprometimentos éticos. Com base nesses resultados, o estudo fornece recomendações para marcas de moda rápida priorizarem a transparência, alavancarem as tecnologias de IA para o desenvolvimento de produtos sustentáveis, inovarem continuamente e integrarem considerações éticas na implementação de IA.



**Palavras-Chave:** Inteligência Artificial (IA), Indústria da Moda Rápida, Personalização impulsionada por IA, Sustentabilidade, Compromisso do Consumidor, Bem-estar

JEL: M31 – Marketing

JEL: M39 – Marketing and Advertising: Other

## Index

## Figure Index



## Table Index

# Chapter 1 – Introduction

## 1.1. The Relevance of the Topic

The fast fashion industry is in a state of constant flow, driven by rapid technological advancements that are reshaping consumer experiences. Among these innovations, Artificial intelligence (AI) stands out, enabling highly personalized interactions and significantly influencing consumer behaviors. As AI-driven personalization becomes increasingly prevalent, it is crucial to understand its impact on consumer behavior and sustainability within fast fashion marketing. The convergence of consumer behavior dynamics, technological innovation, and environmental sustainability is pivotal in shaping the future of the fast fashion industry. Exploring these interconnected themes is essential to grasp the industry's evolving dynamics and emerging challenges, making this dissertation highly relevant and timely.

## 1.2. Contextualization

Against the backdrop of globalization, digitization, and climate change, the fast fashion industry operates within a complex ecosystem influenced by a myriad of socio-economic, cultural, and environmental factors. Supply chain intricacies, labor practices, technological disruptions, and shifting consumer preferences contribute to an industry landscape with both challenges and opportunities. Recent studies by Bläse et al. (2024), Stringer et al. (2020), Centobelli et al. (2022), Chandra et al. (2022), and Chen et al. (2022) have shed light on different aspects of AI-driven personalization, sustainable practices, and their impact on consumer behavior. These insights pave the way for formulating important research questions. Studying the fast fashion landscape provides an understanding of its complexities and underscores the importance of scholarly inquiry into its underlying dynamics.

## 1.3. Problem Statement, Dissertation Research Questions and Objectives Definition

Despite its wide-reaching influence and economic importance, the fast fashion industry grapples with critical issues surrounding sustainability, ethical sourcing, and consumer engagement. The prevalent model of fast fashion production, characterized by resource-intensive practices and disposable consumption patterns, has faced scrutiny for its adverse environmental impact and social implications. Furthermore, rapid technological advancements have reshaped consumer interactions and market dynamics, presenting new challenges and opportunities for industry stakeholders. Addressing these challenges requires a nuanced understanding of consumer behavior, technological innovation, and sustainability within the fast fashion landscape.

The research problem revolves around understanding the impact of AI-driven personalization on consumer purchasing behavior in the fast fashion industry while taking into account crucial factors such as privacy, data security, and ethical considerations for sustainable marketing strategies. Within this framework, this dissertation places significant emphasis on ethical considerations related to consumer expectations, privacy concerns, and data security intricacies. It aligns with the ethical imperatives claimed by Garcia-Ortega et al. (2023) and sustainable dimensions elucidated by Henkens et al. (2021), contextualizing the contemporary challenges and opportunities of AI in the fast fashion industry. The formulation of research questions is related to the deepening of these ethical and sustainable dimensions, echoing the scholarly discourse articulated by Kumar et al. (2019).

As part of this dissertation, the impact of AI-driven personalization on consumer behavior and related factors in the fast fashion industry is explored, aiming to provide actionable insights to industry managers who seek to enhance marketing strategies through sustainable and ethical practices. By addressing pressing ethical concerns and contributing to the academic discourse on AI's role in marketing, this study endeavors to inspire collective action toward a more sustainable future for the fashion industry.

Accordingly, this research intends to answer:

**RQ1:** To what extent does AI-driven personalization influence consumers' purchase behavior in the fast fashion industry, considering privacy, data security, and ethical factors?

**RQ2:** How do emerging trends and technological advancements, particularly in AI-driven personalization, impact consumer engagement and market dynamics in fast fashion?

**RQ3:** What are the effectiveness and implications of sustainable practices and ethical initiatives in mitigating the environmental footprint of fast fashion, and how can they be integrated into marketing strategies to promote responsible consumption?

### 1.4. Structure of the Dissertation

This dissertation comprises several chapters that systematically delve into various aspects of the research topic. It begins with preliminary sections such as acknowledgments, and abstracts in English and Portuguese, followed by the introduction, which contextualizes the fast fashion landscape and outlines the problem statement, research questions, and objectives. The literature review explores key themes, including the intersection of artificial intelligence (AI) and consumer behavior, ethical considerations, and environmental sustainability. The conceptual framework and hypotheses development chapter lay the theoretical groundwork for the study. Methodology delineates the research methods employed, including construct measurement, questionnaire design, data collection procedures, and sample profile. The results and discussion chapter presents the findings of the study, accompanied by an in-depth analysis and interpretation of the data. Theoretical contributions and managerial implications are then discussed, highlighting the practical significance of the research findings. The conclusions and recommendations chapter synthesizes the key insights, offers concluding remarks, and proposes avenues for future research. The dissertation concludes with a comprehensive list of bibliographical references and appendixes, providing supplementary materials such as the questionnaire, measurement scales, and additional statistical analyses. This structured approach ensures clarity, coherence, and rigor throughout the dissertation, facilitating a comprehensive understanding of the research findings and their implications.

# Chapter 2 – Literature Review

## 2.1. Fast Fashion Landscape

The fast fashion industry has witnessed unprecedented growth driven by major retailers such as H&M and Zara, with projections estimating its value to reach $2.25 trillion by 2025 (Centobelli et al., 2022). Despite its popularity, this industry confronts significant challenges, including supply chain constraints and environmental impact. Thus, this section explores the multifaceted landscape of fast fashion, delving into its environmental and ethical implications, the impact of marketing strategies in fueling consumption, and the need for sustainable practices to effectively address these challenges.

This business model offers a broad range of trendy products through e-commerce platforms, but it faces significant challenges, including supply chain limitations and environmental impact (Santos et al., 2021; Long & Nasiry, 2022). In terms of the environment, the fast-paced production and disposal of fashion items contribute to waste and carbon emissions, which exacerbate environmental concerns (Peters et al., 2021; Rudolph et al., 2023).

The role of marketing in fueling fast fashion consumption and contributing to negative environmental impact has been significant. Strategies aimed at eliciting emotional responses from consumers have been effective, as evidenced by research conducted by Salem and Salem (2021). While social media platforms have amplified brand visibility, the importance of effective targeting cannot be overstated. The phenomenon of Fear of Missing Out (FOMO) and celebrity endorsements have been identified as key drivers of impulsive purchasing, according to studies conducted by Bläse et al. (2024).

Despite the widespread appeal of fast fashion marketing, it's important to acknowledge the ethical implications along with the environmental implications it presents (Garcia-Ortega et al., 2023). Compounding this issue is the emotional attachment and desire for self-expression that can lead to brand loyalty (Mrad et al., 2020), making it even more difficult to promote sustainable consumption. To overcome these challenges, a multi-level approach is necessary, which includes educating consumers, implementing sustainable marketing practices, and enacting regulatory interventions (Atik & Ertekin, 2023).

According to Chandra et al. (2022), each customer is unique and has their own set of needs, preferences, emotions, desires, and motivations that should be considered when creating personalized marketing strategies. This approach goes beyond traditional segmentation, focusing on individual customer context and uniqueness. By using technologies such as AI, big data, and IoT, companies can tailor their marketing efforts to better engage and satisfy customers (Chandra et al., 2022; Kumar et al., 2019). This is particularly relevant for fast fashion, where rapid trend adaptation can benefit from personalized marketing to improve customer relationships. Firms that leverage AI for personalization gain a competitive advantage and enhance customer retention, as noted by Kumar et al. (2019).

In sum, the fast fashion industry's impressive expansion presents a range of possibilities and obstacles. The rapid pace of trends and marketing tactics contribute to increased consumption but also intensify environmental and ethical issues. Addressing these challenges necessitates multi-faceted approaches, such as promoting consumer awareness and sustainable marketing techniques. Utilizing personalized marketing, utilizing cutting-edge technologies like AI, can unlock tremendous potential for customized strategies and deeper customer connections.

### 2.2. AI and Consumer Behavior

In the following section, we shift our focus to the integration of AI in enhancing customer experience, personalization, and marketing efficiency within the fast fashion industry. It explores how AI-driven insights into consumer behavior inform personalized marketing strategies, highlighting the potential of AI to address environmental challenges while catering to dynamic consumer preferences.

The rise of Industry 4.0 has given way to a new era of transformative technologies such as Artificial Intelligence (AI), which is now at the forefront of the fast fashion industry's evolution (Santos et al., 2021; Verma et al., 2021). With AI's ability to mimic human-like tasks through machine learning, it has become a valuable asset in enhancing customer experience and streamlining efficiency, while also reshaping marketing strategies (Kumar et al., 2019). AI's integration in fast fashion extends to customer engagement, personalization, and marketing efficiency, all of which align with the evolving preferences of today's consumers (Verma et al., 2021; Kumar et al., 2019).

Insights into consumer behavior, including the Fear of Missing Out (FOMO) and celebrity endorsements, are utilized to inform AI-powered personalization strategies, resulting in tailored marketing approaches (Bläse et al., 2024; Chandra et al., 2022). Additionally, the significant influence of social media on shaping consumer behavior highlights the multidimensional effects of AI-driven personalization (Salem & Salem, 2021).

Globally, the implementation of AI-powered personalization in fast fashion marketing has the potential to address pressing environmental challenges, improve customer engagement, and effectively cater to dynamic consumer preferences, all grounded in a comprehensive understanding of consumer behavior. As the industry continues to evolve, the integration of AI technology is expected to significantly shape its future trajectory.

### 2.3. Consumer Engagement and Well-being in AI Marketing

In the world of AI-powered marketing, customized strategies are essential for effectively engaging consumers and fostering well-being, particularly in the fast-paced fashion industry where consumer preferences change rapidly. Accordingly, this section delves into the crucial role of personalized marketing in meeting individual needs while aligning with ethical concerns and corporate social responsibility (CSR) principles. It explores how AI-driven initiatives not only enhance consumer engagement but also promote overall societal well-being through transparent communication and accountability.

According to Centobelli et al. (2022), personalized marketing is essential for effectively meeting individual needs. By utilizing AI, businesses can tailor their approaches, reduce waste, and align with ethical concerns, ultimately building consumer engagement and trust (Garcia-Ortega et al., 2023; Roozen & Raedts, 2020; Rudolph et al., 2023). Understanding how consumers respond to personalized marketing is vital, with factors such as engagement, trust, and ethical considerations playing significant roles (Chen et al., 2022; Stringer et al., 2020).

Moreover, the influence of AI extends beyond just marketing and encompasses the broader spectrum of well-being. Du and Sen (2023) propose a CSR-oriented (Corporate Social Responsibility) methodology for AI development that prioritizes the welfare of all stakeholders. Additionally, Pataranutaporn et al. (2021) accentuate the role of AI in elevating personal wellness, whereas Singh and Singh (2023) delve into its significance in comprehending subjective well-being. Moreover, Musikanski et al. (2020) emphasize AI's impact on community well-being and the necessity for comprehensive frameworks to evaluate its effects.

The factors that influence consumer engagement with AI are complex and multifaceted. According to research conducted by Budd and Spencer (1985), personal experiences can play a significant role in shaping environmental concerns, while Chin et al. (2020) suggest that brand credibility and the influence of endorsers can impact purchase intentions. Servera-Francés and Piqueras-Tomás (2019) emphasize the importance of CSR in enhancing consumer value, trust, and loyalty, and Bouman et al. (2021) explore how personal and group values can influence climate action.

In sum, the convergence of AI-based marketing and consumer well-being emphasizes the importance of tailored approaches that align with ethical conduct and CSR principles. It is imperative to understand the factors that influence consumer responses and AI encounters to promote engagement, reliability, and sustainability, thereby enhancing overall societal well-being.

### 2.4. Credibility and Trust Online

In the field of AI-driven and customized marketing, building trust is paramount for cultivating lasting customer connections and navigating the ever-evolving online landscape, notably within the fast fashion industry. This section explores strategies for developing trust and credibility online, emphasizing the importance of transparent communication and ethical practices. It examines the intricate relationship between trust, brand credibility, and consumer behavior, underlining the need for sustained customer trust and loyalty across various digital platforms.

As AI becomes increasingly prevalent across industries such as retail and fast fashion, it is crucial to implement effective trust-building strategies. Research by Verma et al. (2021), Kumar et al. (2019), and Chen et al. (2022) highlight the transformative impact of AI, including optimizing customer engagement, refining decision-making processes, and revolutionizing marketing tactics. Parker-Strak et al. (2020) emphasize the necessity of effective communication and collaboration for building trust, especially in the multifaceted field of AI-powered marketing.

The fast fashion industry is affected by various elements that impact consumer trust, engagement, and loyalty. According to Roozen & Raedts (2020), unfavorable publicity can have a profound effect on brand loyalty, while Stringer et al. (2020) stress the significance of ethical considerations in shaping consumer trust. Furthermore, Chen et al. (2022) have highlighted that consumers' views on AI in marketing communication play a crucial role in determining trust and engagement levels.

The research conducted by Manzoor et al. (2020) highlights the vital importance of trust in e-commerce, highlighting the need for a harmonious fusion of personalization and sustained trust in online marketing tactics. Moreover, Bläse et al. (2024) delve into the complex association between trust and brand credibility within the context of personalized marketing, emphasizing the fundamental role of trust in molding consumer conduct and nurturing strong customer connections.

Globally, the insights presented reveal the significance of credibility and trust-building measures in effectively navigating the ever-evolving landscape of AI-driven and personalized marketing. This highlights the crucial need for transparent communication, accountability, and ethical practices to foster sustained customer trust and loyalty across various digital platforms.

### 2.5. Environmental Sustainability and AI

The intersection of environmental sustainability and AI presents promising opportunities for the fast fashion industry to address pressing challenges. Hence, this section explores how AI-powered solutions can mitigate environmental impact while meeting consumer needs responsibly. It delves into the ethical and sustainable practices within fast fashion, stressing the significance of upholding ethical conduct and preserving brand trustworthiness.

Recent research has brought to the forefront the critical issues of the industry's environmental impact and ethical concerns. Bläse et al. (2024) highlight the role that consumer behavior, fueled by the fear of missing out (FOMO), plays in promoting unsustainable practices that worsen environmental challenges. In a similar vein, Atik and Ertekin (2023) point out the industry's trend-driven cycle that perpetuates excessive consumption, posing significant hurdles to achieving sustainability goals.

Amid challenges faced by the fast fashion industry, personalized AI solutions offer a vital step forward in its development. Research conducted by Chandra et al. (2022) and Kumar et al. (2019) highlights the significance of AI in improving inventory management, refining pricing strategies, and recommending products that align with unique preferences. By enhancing customer satisfaction and mitigating environmental impact, the incorporation of AI is a promising approach for the industry's continued progress.

Additionally, the use of AI-powered personalization presents opportunities to promote sustainable practices by reducing impulsive buying tendencies (Bläse et al., 2024) and encouraging eco-friendly consumer choices (Atik & Ertekin, 2023). This integration supports the fashion industry's objective of fostering sustainability while meeting consumer needs.

Ethical and sustainable practices in fast fashion are multi-faceted, as highlighted by various studies. Strategies presented by Garcia-Ortega et al. (2023), Parker-Strak et al. (2020), and Rudolph et al. (2023) include transparency, circular product development, ethical sourcing, and collaboration to promote sustainability and ethical behavior.

Thus, ethical concerns and brand loyalty are heavily influenced by consumer values and perceptions, as evidenced by research studies conducted by Stringer et al. (2020), Roozen and Raedts (2020), and Bläse et al. (2024). These findings emphasize the significance of upholding ethical standards and preserving brand trustworthiness to meet the constantly evolving demands of consumers.

In sum, the recent research conducted on the fast fashion industry provides a comprehensive understanding of the intricate dynamics of ethical and sustainable practices. Through the integration of AI-driven personalization and the promotion of sustainability initiatives, the industry can effectively address environmental challenges while simultaneously meeting consumer demands responsibly. These insights offer a promising way for the industry to navigate the current sustainability crisis, and fashion businesses must adopt such practices to ensure the long-term sustainability of the industry.

### 2.6. Ethical and Privacy Considerations

The rise of AI-driven personalization in fast fashion has also sparked concerns about the ethical use of consumer data. Thus, this section examines the importance of privacy safeguards and ethical retailing practices in promoting sustainability and consumer trust. It underscores the need for strong regulatory frameworks and transparent communication to address evolving privacy concerns effectively.

Henkens et al. (2021) emphasize the importance of privacy safeguards in smart systems, promoting ethical data utilization and protecting personal privacy. Ethical retailing, as demonstrated by Rudolph et al. (2023), effectively utilizes AI-driven personalization to promote sustainability, offering valuable insights for fast fashion marketing. Meanwhile, Takyar (2023) highlights AI's transformative potential across industries, particularly in promoting sustainability and ethical practices in fast fashion. To ensure responsible AI use and protect consumer rights in the fast fashion sector, regulatory frameworks are essential, as discussed by Rudolph et al. (2023), Cloarec (2022), and the European Commission (2023).

Effective privacy controls serve an essential purpose in combating data manipulation and preserving consumer trust, as noted by Cloarec (2022). The fast fashion industry is subject to the influence of rapid product development and negative publicity, which can impact consumer behavior (Parker-Strak et al., 2020; Roozen & Raedts, 2020). Chen et al. (2022) emphasize the connection between ethical considerations and privacy in consumer decision-making, while Bläse et al. (2024) highlight how privacy concerns stemming from FOMO and AI marketing can impact purchasing behavior. Given the evolving landscape of fast fashion, brands and marketers must address these privacy concerns.

In sum, it's crucial to strike a balance between technological progress and ethical principles, as well as privacy protection. The aforementioned studies emphasize the significance of strong regulatory frameworks, ethical principles, and privacy measures to tackle critical issues surrounding data privacy, customer welfare, and ethical retail practices. By prioritizing these factors, stakeholders can encourage responsible corporate behavior, build consumer trust, and uphold ethical benchmarks in the dynamic domain of fast fashion.

### 2.7. Well-being through AI

The use of AI-driven personalization in the fast fashion industry has been shown to hold immense potential in promoting consumer well-being. Therefore, this section explores the interrelated contribution of AI in enhancing operational efficiencies and augmenting product quality while fostering consumer satisfaction and ethical conduct. It emphasizes the importance of striking a balance between AI-driven efficiency and human-centered approaches to advance overall consumer well-being.

The multifaceted and interconnected involvement of AI-powered personalization in promoting consumer well-being is underscored by ethical considerations and sustainable approaches, as noted by Rudolph et al. (2023) and Atik and Ertekin (2023). These best practices not only align with consumer ethical concerns but also address sustainability challenges in the fast fashion industry.

Takyar (2023), however, stresses the transformative capacity of artificial intelligence (AI) in various industries, accentuating how it can enhance efficiency and augment product quality. In the fast fashion sector, AI-driven personalization techniques provide customized product recommendations, which can reduce the number of returns, increase customer loyalty, and optimize inventory management (Chandra et al., 2022; Kumar et al., 2019).

Parker-Strak et al. (2020) have drawn attention to the benefits of personalized marketing strategies, which not only increase customer engagement but also promote sustainability by encouraging eco-friendly choices. AI-generated insights have proven to be a valuable tool in decision-making, enabling businesses to enhance their pricing strategies and operational efficiency (Kumar et al., 2019; Chandra et al., 2022).

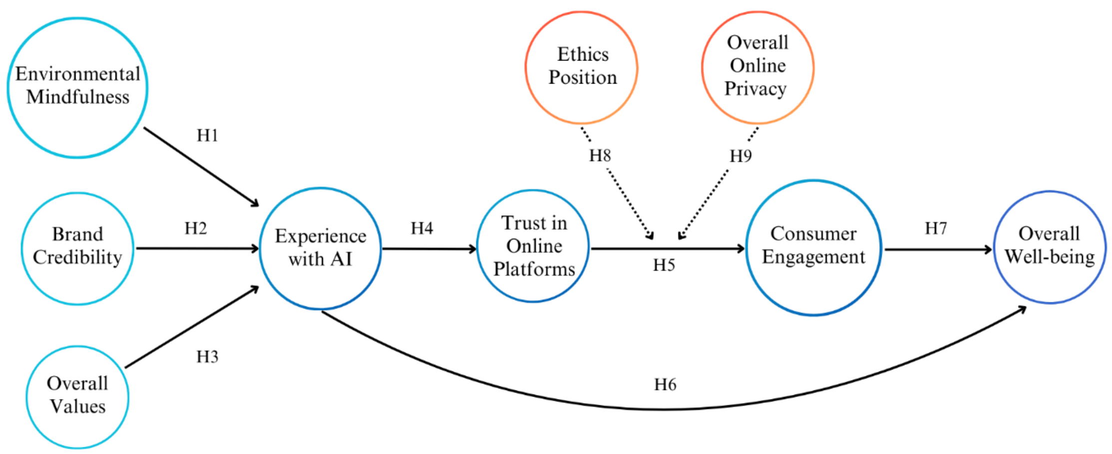
According to findings by Prentice and Nguyen (2020), even though AI can enhance operational efficiencies, individuals tend to favor personalized interactions with human staff. The study highlights the significance of emotional intelligence in moderating service experiences and promoting a favorable consumer experience. Therefore, it is crucial to maintain a balance between AI-driven efficiency and the human touch to cater to the needs of consumers. It is imperative to comprehend the intricate interplay between human and AI-powered service experiences to foster favorable consumer well-being. By recognizing the preferences of consumers and leveraging emotional intelligence, organizations can effectively capitalize on the potential of AI while placing consumer satisfaction and ethical conduct at the forefront of their operations (Prentice & Nguyen, 2020).

Therefore, the investigation into how AI-driven personalization affects consumer well-being underscores the significance of implementing ethical, sustainable, and human-centered approaches. Although AI presents valuable advantages such as improved operational efficacy and tailored suggestions, it is vital to maintain a balance with human involvement to cater to consumer preferences and cultivate favorable encounters. By placing consumer satisfaction, ethical principles, and emotional intelligence at the forefront, companies can effectively utilize AI to advance well-being while tackling sustainability obstacles.

## Chapter 3 – Conceptual Framework and Hypotheses Development

This chapter delves into the conceptual framework and its associated hypotheses, which serve as the foundation of the research. The framework plays a crucial role in shaping the structure of the study, providing essential guidance to the empirical investigation through formulated hypotheses. A robust foundation has been established by thoroughly analyzing previous research in the literature review, enhancing understanding of the variables and their interrelationships. This method of creating and validating hypotheses within a well-defined conceptual framework aligns with academic standards, ensuring the rigor and validity of the study, and contributes to the enhancement of knowledge in the Marketing field. Figure 1 visually presents the established conceptual framework, providing a clear representation of the ideas presented, and thereby facilitating a more comprehensive understanding of the research.

*Figure 3.1 – Proposed Conceptual Framework*




*Source: Author's own elaboration*

As mentioned in the presented literature review, consumers are increasingly conscious of the environmental impacts associated with fast fashion (Santos et al., 2021; Rudolph et al., 2023). This growing environmental mindfulness has resulted in a surge in demand for sustainable practices within the fashion industry. As such, companies that demonstrate a commitment to environmental sustainability through their AI-powered initiatives are likely to enhance consumer experiences and foster positive brand perceptions. Chandra et al. (2022) argue that

AI has the potential to improve sustainability by providing consumers with personalized recommendations for eco-friendly choices. Consequently, the following hypothesis is proposed:

**H1:** Environmental Mindfulness (EnvMind) positively influences Experience with AI (ExpAI).

Brand credibility emerges as a critical factor that significantly influences consumers' perceptions and attitudes toward the adoption of AI-driven experiences in the fast fashion industry, as evidenced in recent studies (Chen et al., 2022). When consumers perceive a brand as credible and trustworthy, they are more likely to trust AI recommendations and interactions. However, in cases where there are doubts about a brand's integrity or ethical practices, it can negatively impact the consumer's experience with AI. According to research by Bläse et al. (2024), trust and brand credibility are integral components within personalized marketing contexts. Hence, the following hypothesis is proposed:

**H2:** Brand Credibility (BC) negatively influences Experience with AI (ExpAI).

Consumers' ethics and overall values play a significant role in shaping their perceptions of AI-powered experiences in the fast fashion industry. According to recent studies by Garcia-Ortega et al. (2023) and Rudolph et al. (2023), the perception and importance of personal beliefs and values hold considerable weightage in molding consumer attitudes toward AI-driven initiatives. Consumers who prioritize ethical behavior, sustainability, and transparency are more likely to have positive experiences with AI-powered initiatives that align with their values. Roozen and Raedts (2020) propose that ethical considerations play a vital role in shaping consumer trust. Based on this, the following hypothesis is proposed:

**H3:** Overall Values (OV) positively influence Experience with AI (ExpAI).

Drawing upon the aforementioned literature, it has been suggested that a positive experience with AI-driven initiatives may foster greater trust in online platforms operating within the fast fashion industry (Verma et al., 2021). Specifically, consumers who encounter favorable interactions and receive personalized recommendations through AI-powered mechanisms are likely to develop a sense of trust in the platforms they engage with. To this end, Kumar et al.

(2019) emphasize the efficacy of AI in optimizing customer engagement and decision-making processes. Based on these premises, the following hypothesis is proposed:

**H4:** Experience with AI (ExpAI) positively influences Trust in Online Platforms (TOP).

As per the recent findings of Parker-Strak et al. (2020), trust in online platforms is a key determinant of increased consumer engagement within the fast fashion industry. Positive AI experiences coupled with brand credibility are the driving factors behind the development of trust in such platforms. Consumers who trust these platforms are more likely to actively engage with them, thereby making purchases, providing feedback, and participating in brand activities. The significance of trust in shaping consumer behavior is emphasized by Stringer et al. (2020). As a result, the following hypothesis is proposed:

**H5:** Trust in Online Platforms (TOP) positively influences Consumer Engagement (Eng).

The deployment of Artificial Intelligence (AI) in fast fashion has been found to have a significant impact on consumers' well-being (Takyar, 2023). The implementation of AI-powered personalization has been shown to increase consumer satisfaction, alleviate decision-making stress, and encourage sustainable choices, ultimately leading to improved well-being. Additionally, AI has the potential to optimize inventory management and provide customized recommendations, as noted by Chandra et al. (2022). In light of these findings, the following hypothesis is proposed:

**H6:** Experience with AI (ExpAI) positively influences Overall Well-being (OW).

Following Prentice and Nguyen (2020), active consumer engagement, which involves meaningful participation with brands and platforms, is believed to have a positive impact on an individual's overall well-being. This is attributed to the fact that engaged consumers tend to derive greater satisfaction from their interactions, leading to a sense of fulfillment and an overall sense of well-being. Moreover, in the context of fast fashion, Musikanski et al. (2020) highlight the importance of community well-being. For this reason, the following hypothesis is proposed:

**H7:** Consumer Engagement (Eng) positively influences Overall Well-being (OW).

Consumers' ethical positions, including their beliefs regarding sustainability and responsible consumption, have been found to play a crucial role in moderating the relationship between trust in online platforms and consumer engagement. Specifically, it has been observed that individuals with strong ethical positions tend to engage more actively with platforms they trust, particularly when they perceive these platforms to be aligned with their values (Chin et al., 2020; Bläse et al., 2024). Indeed, Bouman et al. (2021) have explored how personal values can impact climate action. Due to this, the following hypothesis is proposed:

**H8:** Ethics Position (Eth) moderates the relationship between Trust in Online Platforms (TOP) and Consumer Engagement (Eng).

The perception of online privacy among consumers plays a vital role in moderating the relationship between trust in online platforms and consumer engagement (Chen et al., 2022; Bläse et al., 2024). When consumers feel that their privacy is sufficiently safeguarded by the platform, they are more likely to trust and engage with it. Conversely, apprehensions regarding online privacy can restrain engagement, even if trust has been established. Cloarec (2022) highlights the significance of privacy controls in maintaining consumer trust. Therefore, the following hypothesis is proposed:

**H9:** Overall Online Privacy (OPriv) moderates the relationship between Trust in Online Platforms (TOP) and Consumer Engagement (Eng).

The hypotheses presented in this study are founded on a comprehensive literature review that provides valuable insights into the intricate dynamics of AI-driven experiences, consumer behavior, trust, ethics, and well-being within the fast fashion industry. Through an empirical exploration of these hypotheses via statistical analysis, this study aims to contribute to a deeper understanding of the factors that shape consumer engagement, trust, and well-being in the context of AI-powered marketing. The forthcoming chapter, Methodology, will detail the research design and methods used in this study to carry out this investigation.

# Chapter 4 – Methodology

As previously stated, this research paper intends to investigate the implications of AI-driven personalization on consumer behavior and sustainability in the fast fashion industry, focusing on marketing dynamics. To answer the aligned overarching thesis objective and research questions, there were developed a conceptual framework and hypotheses, upon the literature review.

Consequently, this study implemented various research methods within a quantitative approach, by crafting a questionnaire on Qualtrics, a web-based tool for creating surveys and generating reports, and sharing it on Prolific, an online research platform where participants can be recruited quickly and reliably. It was designed based on the already presented conceptual framework and had the goal of recognizing patterns from the collected results, which allows for extrapolating them and testing the hypotheses. The target participants on Prolific were 18-year-old or older respondents who currently reside in the United States of America and have utilized an algorithm or device incorporating AI.

Moreover, the study primarily leveraged statistical analysis of data treated through SmartPLS 4. Additionally, the sociodemographic characteristics of the respondents were analyzed through IBM SPSS Statistics, producing frequency and descriptive data (Appendix C).

### 4.1. Construct Measurement

To ensure a comprehensive assessment of the various dimensions being studied, a questionnaire was designed using sixteen original measurement scales from reputable journals. After careful consideration, fifteen of those scales were adapted to suit the specific needs of this study. The remaining scale, Ethics Position, was retained in its original form, given its relevance and reliability from the source.

Furthermore, one of those measurement scales was included to test the Common Method Bias (CMB), which assesses its effects on the other constructs and identifies and analyzes potential bias. According to Podsakoff et al. (2003), the Common Method Bias (CMB) can be defined as a phenomenon commonly observed in studies where data for both independent and dependent variables are sourced from the same individual within the same measurement context, utilizing similar item context and characteristics. The authors (2003) also mention that the sources of CMB include the shared usage of the same item for both variables, errors within measurement items, and contextual influences like social desirability or leniency bias during the acquisition of measurement instruments. To mitigate CMB, researchers can employ various strategies such as procedural remedies, statistical controls, or the use of multiple data sources, thereby enhancing the accuracy and reliability of research findings (Podsakoff et al., 2003).

Thus, the questionnaire focused on ten constructs, which incorporate the conceptual framework. These constructs are Blue Color Marker (BL), Brand Credibility (BC), Consumer Engagement (Eng), Environmental Mindfulness (EnvMind), Ethics Position (Eth), Experience with Artificial Intelligence (ExpAI), Overall Online Privacy (OPriv), Overall Values (OV), Overall Well-being (OW), and Trust in Online Platforms (TOP).

It is pertinent to mention that EnvMind, OPriv, and OW were divided into two dimensions each with different measurement items, while OV was divided into four dimensions. The remaining constructs had only one dimension each, hence they were named accordingly.

All of the constructs were measured using a 7-point Likert Scale, where participants had to answer each item from 1 (Strongly Disagree) to 7 (Strongly Agree). The respondents answered a total of 139 items, which were organized based on their construct dimensions, as seen in Table 4.1:

*Table 4.1 - Measurement Likert Scales*

| Constructs | Dimensions | No. of Items | Type | Source |
|---|---|---|---|---|
| **Blue Color Markers (BL)** | Blue Color Marker (BL) | 4 | Adapted | Williams et al. (2010) |
| **Brand Credibility (BC)** | Brand Credibility (BC) | 6 | Adapted | Baek & King (2011) |
| **Consumer Engagement (Eng)** | Consumer Engagement (Eng) | 8 | Adapted | So et al. (2014) |
| **Environmental Mindfulness (EnvMind)** | Environmental Awareness (EAw) | 5 | Adapted | Gadenne et al. (2008) |
| | Environmental Concern (EC) | 16 | | Minton & Rose (1997) |
| **Ethics Position (Eth)** | Ethics Position (Eth) | 18 | Original | Muncy & Vitell (1992) |
| **Experience with AI (ExpAI)** | Experience with AI (ExpAI) | 14 | Adapted | Chen et al. (2021) |
| **Overall Online Privacy (OPriv)** | Online Privacy Concern (PCon) | 18 | Adapted | Hong & Thong (2013) |
| | Online Privacy Policies (PPol) | 7 | | Pitofsky et al. (1998) |
| **Overall Values (OV)** | Perceived Quality Value (PQV) | 6 | Adapted | Walsh et al. (2014) |
| | Perceived Social Value (PSV) | 4 | | |

| Constructs | Dimensions | No. of Items | Type | Source |
|---|---|---|---|---|
| | Perceived Emotional Value (PEV) | 5 | | |
| | Personal Values (V) | 9 | | Kahle (1983) |
| **Overall Well-being (OW)** | Psychological Well-being (PW) | 5 | Adapted | Viswanathan et al. (2009) |
| | Consumer Well-being (CW) | 10 | | Lee et al. (2002) |
| **Trust in Online Platforms (TOP)** | Trust in Online Platforms (TOP) | 4 | Adapted | McKnight et al. (2002) |
| | | Total = 139 | | |

*Source: Own elaboration*

### 4.2. Questionnaire

The questionnaire was designed for individuals residing in the USA, aged 18 years or above, and who have used an AI-powered device or algorithm. All the questions in the questionnaire were mandatory and aimed to gather personal responses on various aspects related to AI-driven personalization in fast fashion. The questionnaire was distributed via the Prolific platform and emphasized the importance of honest responses by clarifying that there were no 'right' or 'wrong' answers.

At the beginning of the questionnaire, the users were asked to provide their Prolific code, and, at the end of it, they had to copy the end code provided back to Prolific. This secure process helped to connect the Qualtrics and Prolific platforms databases, contributing positively to the reliability of the collected data.

The questionnaire began with three questions on sociodemographic characteristics, including respectively in this order age, gender, and highest education level, to further analyze and describe the sample. These were followed by two control questions that ensured the respondents belonged to the target group. This means that only confirmed participants who currently reside in the USA and have prior experience with AI were included in the study. If the respondents did not meet these requirements, they were redirected to the end of the survey and eliminated from the study.

The remaining questions were assessed through a Likert-type scale. Participants had to choose answers ranging from 1 (Strongly Disagree) to 7 (Strongly Agree) regarding their level of agreement for each item presented to them. These items were categorized under different constructs, as mentioned above. Both control and Likert-type scale questions about constructs were set to be random to reduce unintended bias and improve data collection.

The complete questionnaire can be seen in Appendix A.

### 4.3. Data Collection and Procedures

As outlined earlier, the questionnaire was developed on Qualtrics and all questions were mandatory. Afterward, it was published online on Prolific for three days. During this period, the questionnaire was activated and paused at different times of the day in the Lisbon time zone (GMT) – morning, afternoon, and night. This translated to slight differences in the USA time zone depending on the participants' location, either GMT-5, GMT-6, GMT-7, or GMT-8. The aim was to capture different online respondents available.

Before answering the questionnaire, the participants were given an estimation that it would take approximately 10 minutes to complete. This estimation was based on the Qualtrics time prediction, on the pre-test, and on the fact that most residents in the USA would either be native English speakers or proficient in it. Additionally, the participants were informed about the amount of money to be paid by the researcher, the purpose of the study, and that all data recorded would be collectively analyzed, and participants' anonymity would be ensured for academic purposes.

After the respondents completed the questionnaire anonymously, their answers were reviewed and confirmed on Prolific. To confirm the responses, each respondent was provided with a unique Prolific validation code at the end of the questionnaire. The code was then required to be pasted back into the platform by the respondent for validation to facilitate the researcher's review. Additionally, the submission details on both Qualtrics and Prolific were checked to ensure the accuracy, validity, and completion of the answers. The respective participant who completed the questionnaire was accepted and paid.

It is crucial to note that the decision to gather only the gender, age, and highest education level of the participants was made to ensure that the collected demographic information sufficiently characterizes the sample while minimizing respondent burden. These variables were chosen based on their relevance to the study objectives and their potential to provide valuable insights into the characteristics of the participants. Segmenting and analyzing the sample by key sociodemographic factors is facilitated by fundamental variables of gender and age. Additionally, the highest education level serves as a substitute for socioeconomic status and educational background, providing further context for understanding the sample composition. By focusing on these essential demographic variables (Appendix B), the study aims to capture meaningful differences and patterns within the sample that are pertinent to the research objectives, while avoiding unnecessary complexity and respondent fatigue.

A total of 223 valid responses were received from the targeted group. The collected responses were inputted into IBM SPSS Statistics 28 to generate output on the frequency and descriptive statistics regarding the sample's sociodemographic characteristics, across age, gender, highest education levels, and the answers on “Other” in Highest Education Levels, and then Likert scale measurements constructs (Appendix C). Notably, the measurement scales of the sociodemographic characteristics were organized as presented in Appendix B. Moreover, to test the conceptual framework, to compare other details regarding the CMB construct, Blue Color Markers (BL), and to ensure data reliability and validity, the same data was then uploaded to SmartPLS 4.

Finally, all the answers were evaluated using the BL construct to ensure unbiased results. This was accomplished by comparing the statistics generated from the questionnaire data with and without the Blue Color Markers during the PLS calculations, specifically through Partial Least Squares Structural Equation Modeling (PLS-SEM) algorithms.

### 4.4. Pre-test

Before spreading the questionnaire, this was subjected to a pilot test to refine its effectiveness and relevance. The pre-test aimed to identify and address any potential issues with clarity, wording, interpretation, order, and randomization of the questions, as well as the overall functioning and estimated length of the questionnaire.

It only faced modifications concerning the linkages between the utilized platforms. Rather than automatically transferring participants from the Qualtrics questionnaire to the Prolific completion page, it was advised to display the completion code. In this manner, respondents had to manually copy and paste the code to Prolific.

This modification was implemented to mitigate informatic errors in the redirection process and enhance the accuracy of the data of the participants who have completed the questionnaire. This alteration also aimed to simplify the final step of the process, thus making it more convenient.

### 4.5. Sample Profile

The data collected from the questionnaire is derived from a varied group of individuals, totaling 223 participants. All of them were sourced from the Prolific platform where they were offered monetary compensation for their participation, making the data collection processes faster and reliable.

Moreover, the chosen search filters on the platform ensured that all participants were currently residing in the USA, which was also confirmed by the residence control question included in the questionnaire. The main purpose of targeting individuals for this study is to ensure that the majority of participants are native English speakers or proficient in the language, as English is the primary language of this study. This will result in more accurate responses, given the intricacy and length of the questionnaire, as well as the complexity of this master dissertation topic and research goals. Some of the questions in the survey are similar and may require more focus and understanding.

Additionally, all participants involved in the study are required to be at least 18 years of age, as per the guidelines set by Prolific. This is not only a necessary condition for the thoroughness of this study, but also a requirement that participants must have previously used an algorithm or device that incorporates Artificial Intelligence. This was emphasized as a core prerequisite before the start of the questionnaire and was also confirmed by the experience control question at the beginning of it.

Thereby, the sampling method used to gather respondents involved a combination of Convenience Sampling and Purposive Sampling. On one hand, Convenience Sampling was used to select participants based on the platform's accessibility, ease of use, and the ability to obtain reliable and prompt responses from the participants. Additionally, availability played a role in selecting participants, as those on the Prolific platform were willing and ready to participate in the study. On the other hand, Purposive Sampling was also used to select participants based on specific characteristics, such as being at least 18 years old, residing in the USA, and having prior experience with AI technologies.

In terms of demographics, the sample exhibits an unbalanced gender distribution, with the majority (61.9%) identifying as female. while 34.5% identified as male, followed by 1.8% identifying with other and 1.8% selecting “Prefer not to say”.

To facilitate the data analysis of age, there were created six age groups (see Appendix D).  Age distribution shows a predominant presence of adults aged 25 to 34 years old (32.7%), which implies that the Millennials generation is the most represented one. The number of participants aged 18 to 24 years old and 45 to 54 years old was even lesser (both generations Z and X accounting for 15.7%). Additionally, there were also some adults aged 35 to 44 years old (14.3%), including mostly Millenials, but even fewer aged 55 to 64 years old (11.2%), followed by the older participants aged 65 years old or older (10.3%). This means the Boomer generations and older ones are the least representative ones.

The education levels of the respondents vary, with the most (43%) having a bachelor's degree as their highest level of education. More than half of that group (22.4%) also hold a master's degree. A significant portion of the respondents (18.4%) reported having only a high school education, while the remaining options scored less than 10%. Specifically, 8.5% reported having completed college, 4.9% a doctoral degree, and 2.7% selected "other" as their highest education level. In addition, for the small percentage of respondents who selected "Other" as their highest level of education, 50% mentioned that they had attended some college but did not obtain a diploma. Among the rest, 33.3% mentioned completing technical college, while one person stated that they had earned an associate degree.

Overall, the sample provides a diverse representation of individuals with varying sociodemographic characteristics, enabling a thorough analysis of the study objectives. Further details can be found in Table 4.2.

*Table 4.2 - Sociodemographic Profile of Sample Size*

| Gender | Frequency | Percentage (%) |
|---|---|---|
| Male | 77 | 34.5 |
| Female | 138 | 61.9 |
| Other | 4 | 1.8 |
| Prefer not to say | 4 | 1.8 |
| **Age Groups** | **Frequency** | **Percentage (%)** |
| 18-24 | 35 | 15.7 |
| 25-34 | 73 | 32.7 |
| 35-44 | 32 | 14.3 |
| 45-54 | 35 | 15.7 |
| 55-64 | 25 | 11.2 |
| 65 or older | 23 | 10.3 |
| **Highest Education Levels** | **Frequency** | **Percentage (%)** |
| Less than high school | 0 | 0 |
| High school degree or equivalent (e.g. GED) | 41 | 18.4 |
| College | 19 | 8.5 |
| Bachelor degree | 96 | 43 |
| Master degree | 50 | 22.4 |
| Doctorate degree (PhD.D) or higher | 11 | 4.9 |
| Other – total | 6 | 2.7 |
| Other - Technical/technical college | 2 | 33.3 |
| Other - Some college | 3 | 50 |
| Other - Associate's degree | 1 | 16.7 |

*Source: Own elaboration based on SPSS outputs*

# Chapter 5 – Results and Discussion

This chapter combines research findings with theoretical insights to conclude the impact of AI-driven personalization on consumer behavior and sustainability in the fast fashion industry. Specifically, it seeks to investigate factors that influence consumers' experience with artificial intelligence and how it affects their well-being, as well as the complex interactions between consumer values, trust, engagement, privacy, brand credibility, environmental mindfulness, and ethical considerations in the fast fashion landscape. The goal is to gain a deeper understanding of these factors and provide insights to improve customer well-being and add value through marketing.

The chapter will present the results of the research, analyze the questionnaire data, and discuss the findings, as well as assess potential bias through the Common Method Bias. Additionally, it will provide a discussion that integrates the theoretical contributions and managerial implications of the study. By consolidating theoretical knowledge with quantitative research results, this chapter aims to draw comprehensive conclusions about the topic of the study.

## 5.1. Data Analysis

A comprehensive methodology was employed to analyze the collected data, employing IBM SPSS Statistics 28.0.0.0 for broad analysis and SmartPLS 4 for more detailed examination. SPSS was chosen for its versatility, allowing for a range of statistical analyses, from basic descriptive statistics to complex modeling. Initially, descriptive statistics were conducted to gain an overview of the data features. Subsequently, PLS was utilized for various statistical calculations, including the Partial Least Squares Structural Equation Modeling (PLS-SEM) algorithm and Bootstrapping.

The PLS-SEM algorithm facilitates the examination of research hypotheses by assessing the relationships within the proposed model. Additionally, Bootstrapping was employed to test the significance of various PLS-SEM results. These analyses provided insights into mediation and moderation effects, offering a deeper understanding of both direct and specific indirect effects, as well as interaction effects.

Furthermore, collinearity tests were conducted to assess Common Method Bias, a potential source of bias introduced by the data collection instrument. Addressing common method bias ensures the reliability and validity of the study findings, maintaining the integrity of the data analysis process (Podsakoff et al., 2003). This rigorous approach enhances confidence in the study outcomes, allowing for robust interpretations of the results.

### 5.1.1. Descriptive Statistics

In analyzing the data, a descriptive statistical examination was conducted for the variables outlined in the conceptual framework (Chapter 3), comprising Environmental Mindfulness (EnvMind), Brand Credibility (BC), Overall Values (OV), Experience with Artificial Intelligence (ExpAI), Trust in Online Platforms (TOP), Ethics Position (Eth), Overall Online Privacy (OPriv), Consumer Engagement (Eng), Overall Well-being (OW), and Blue Color Markers (BL). The means and standard deviations of the variables' items were calculated, providing insights into respondents' perceptions and behaviors within the fast fashion industry. Notably, variables such as Environmental Mindfulness (EnvMind) and Overall Values (OV) exhibited varying levels of agreement and dispersion, highlighting the complexity of factors influencing consumer decision-making. For a comprehensive understanding of the data, further details and item-specific analyses can be found in Appendix C.

Finally, the descriptive statistics underscored the diversity of responses and the nuanced nature of consumer attitudes toward AI-driven personalization, sustainability, and online platforms. While some constructs, such as Brand Credibility (BC) and Trust in Online Platforms (TOP), demonstrated moderate levels of agreement, others, like Consumer Engagement (Eng) and Overall Well-being (OW), exhibited greater variability and dispersion. This variability suggests the need for further exploration into the underlying factors shaping consumer perceptions and behaviors in fast fashion. For a detailed breakdown of item-level statistics and a deeper understanding of respondents' viewpoints, Appendix C provides comprehensive tables and analyses for reference.

## 5.2. Results

The forthcoming sub-chapters will provide a comprehensive analysis and detailed explanation of the data and findings gathered from the questionnaire.

### 5.2.1. Construct Reliability and Convergent Validity

*Table 5.1 – Construct Reliability and Convergent Validity*

| Without Markers | | | | |
|---|---|---|---|---|
| | **Cronbach's alpha** | **Composite reliability (rho_a)** | **Composite reliability (rho_c)** | **Average variance extracted (AVE)** |
| BC | 0.948 | 0.949 | 0.959 | 0.795 |
| Eng | 0.965 | 0.966 | 0.970 | 0.803 |
| EnvMind | 0.700 | 0.709 | 0.828 | 0.616 |
| Eth | 0.849 | 0.860 | 0.891 | 0.620 |
| ExpAI | 0.949 | 0.952 | 0.956 | 0.665 |
| OPriv | 0.948 | 0.949 | 0.958 | 0.764 |
| OV | 0.970 | 0.970 | 0.973 | 0.704 |
| OW | 0.963 | 0.967 | 0.968 | 0.752 |
| TOP | 0.902 | 0.924 | 0.931 | 0.771 |

*Source: Own elaboration based on PLS outputs | BC: Brand Credibility, Eng: Consumer Engagement, EnvMind: Environmental Mindfulness, Eth: Ethics Position, ExpAI: Experience with Artificial Intelligence, OPriv: Overall Online Privacy, OV: Overall Values, OW: Overall Well-being, TOP: Trust in Online Platforms.*

Based on Table 5.1, Cronbach's alpha values for each construct are between 0.700 and 0.970, indicating good internal consistency. Additionally, the Composite reliability (rho_a and rho_c) values are also high, ranging from 0.709 to 0.970, which further confirms the reliability of the measures. Additionally, most of the Average Variance Extracted (AVE) values for each construct are above 0.50, with the lowest value being 0.616, suggesting that the constructs are effectively measuring a significant amount of variance in their respective items. Overall, these results provide strong evidence of strong Construct Reliability and Convergent Validity for the measures employed in the study.

### 5.2.2. Discriminant Validity: Fornell-Larcker Criterion

*Table 5.2 – Discriminant Validity: Fornell-Larcker Criterion*

| Constructs | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| BranCredibility **(1)** | **0.892** | | | | | | | | |
| Consumer Engagement **(2)** | 0.600 | **0.896** | | | | | | | |
| Environmental Mindfulness **(3)** | 0.141 | 0.243 | **0.785** | | | | | | |
| Ethics Position **(4)** | 0.262 | 0.424 | 0.218 | **0.788** | | | | | |

| Constructs | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Experience with AI **(5)** | 0.545 | 0.733 | 0.280 | 0.414 | **0.815** | | | | |
| Overall Online Privacy **(6)** | 0.575 | 0.599 | 0.152 | 0.316 | 0.524 | **0.874** | | | |
| Overall Values **(7)** | 0.733 | 0.732 | 0.219 | 0.362 | 0.756 | 0.654 | **0.839** | | |
| Overall Well-being **(8)** | 0.624 | 0.753 | 0.320 | 0.378 | 0.791 | 0.564 | 0.809 | **0.867** | |
| Trust in Online Platforms **(9)** | 0.719 | 0.590 | 0.095 | 0.315 | 0.566 | 0.571 | 0.704 | 0.617 | **0.878** |

*Source: Own elaboration based on PLS outputs. |* ***Note:*** *Bold diagonal values are the results of √AVE and the remaining lower diagonal values represent the factor correlations*

Based on the analysis of the Fornell-Larcker Criterion (as shown in Table 5.2), it is evident that the constructs in the model exhibit satisfactory discriminant validity. This criterion compares the Average Variance Extracted (AVE) of each construct with the squared correlations between that construct and other constructs in the model. The AVE values for each construct are greater than the squared correlations between that construct and all other constructs in the proposed model, indicating that each construct measures a distinct underlying concept and does not significantly overlap with other constructs in the model. This shows that the measurement model has robust discriminant validity, which supports the reliability and interpretation of the relationships between the constructs analyzed.

### 5.2.3. Discriminant Validity: Heterorait-Monotrait Ratio (HTMT)

*Table 5.3 – Discriminant Validity: Heterorait-Monotrait Ratio (HTMT)*

| | BC | Eng | EnvMind | Eth | ExpAI | OPriv | OV | OW | TOP | Eth x TOP | OPriv x TOP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BC | | | | | | | | | | | |
| Eng | 0.626 | | | | | | | | | | |
| EnvMind | 0.170 | 0.287 | | | | | | | | | |
| Eth | 0.279 | 0.448 | 0.278 | | | | | | | | |

| | BC | Eng | EnvMind | Eth | ExpAI | OPriv | OV | OW | TOP | Eth x TOP | OPriv x TOP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ExpAI | 0.566 | 0.763 | 0.345 | 0.446 | | | | | | | |
| OPriv | 0.607 | 0.621 | 0.176 | 0.338 | 0.550 | | | | | | |
| OV | 0.764 | 0.754 | 0.264 | 0.383 | 0.777 | 0.682 | | | | | |
| OW | 0.647 | 0.775 | 0.394 | 0.397 | 0.817 | 0.589 | 0.834 | | | | |
| TOP | 0.773 | 0.612 | 0.111 | 0.336 | 0.596 | 0.598 | 0.744 | 0.650 | | | |
| Eth x TOP | 0.096 | 0.297 | 0.115 | 0.158 | 0.199 | 0.226 | 0.183 | 0.186 | 0.158 | | |
| OPriv x TOP | 0.027 | 0.270 | 0.317 | 0.247 | 0.234 | 0.151 | 0.183 | 0.252 | 0.085 | 0.310 | |

*Source: Own elaboration based on PLS outputs | BC: Brand Credibility, Eng: Consumer Engagement, EnvMind: Environmental Mindfulness, Eth: Ethics Position, ExpAI: Experience with Artificial Intelligence, OPriv: Overall Online Privacy, OV: Overall Values, OW: Overall Well-being, TOP: Trust in Online Platforms.*

Analyzing the provided HTMT values from Table 5.3, all values are below the threshold of 0.9, which is commonly used to indicate adequate discriminant validity. This suggests that the constructs in the proposed measurement model effectively distinguish between different constructs and exhibit acceptable discriminant validity. Therefore, based on the HTMT values, it can be concluded that the measurement model demonstrates satisfactory discriminant validity, indicating that the constructs in the model are distinct from each other and measure different underlying concepts.

### 5.2.4. Cross Loadings

Upon examination of the Cross Loadings table (Appendix D), it is evident that the values are consistent with the item/factor loadings derived from the descriptive statistics analysis. This concurrence indicates a robust alignment in the associations between items and constructs across different analytical methodologies. While the majority of item loading values fall below the 0.7 threshold, signifying prevalent associations with their intended constructs, there are instances where certain values surpass this threshold, albeit remaining below 1. This indicates that each item predominantly has stronger connections with its corresponding construct. Furthermore, descriptive statistics were calculated for each construct, including measures such as mean and standard deviation, providing further insight into the distribution of responses within each construct.

Overall, this analysis of cross-loadings demonstrates that the constructs possess discriminant validity, as each item shows stronger associations with its intended construct compared to others. This underscores the unique nature of each construct, suggesting that they are distinct from one another, with items exhibiting pronounced connections with their intended constructs.

### 5.2.5. Collinearity Statistics (VIF)

*Table 5.4 – Collinearity Statistics (VIF)*

| | BC | Eng | Env Mind | Eth | ExpAI | OPriv | OV | OW | TOP | Eth x TOP | OPriv x TOP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BC | | | | | 2.161 | | | | | | |
| Eng | | | | | | | | 2.164 | | | |
| EnvMind | | | | | 1.052 | | | | | | |
| Eth | | 1.192 | | | | | | | | | |
| ExpAI | | | | | | | | 2.164 | 1.000 | | |
| OPriv | | 1.569 | | | | | | | | | |
| OV | | | | | 2.226 | | | | | | |
| OW | | | | | | | | | | | |
| TOP | | 1.533 | | | | | | | | | |
| Eth x TOP | | 1.149 | | | | | | | | | |
| OPriv x TOP | | 1.152 | | | | | | | | | |

*Source: Own elaboration based on PLS outputs | BC: Brand Credibility, Eng: Consumer Engagement, EnvMind: Environmental Mindfulness, Eth: Ethics Position, ExpAI: Experience with Artificial Intelligence, OPriv: Overall Online Privacy, OV: Overall Values, OW: Overall Well-being, TOP: Trust in Online Platforms.*

When all Variance Inflation Factor (VIF) values for predictor variables in the regression model are below 3.33, it generally indicates minimal multicollinearity among the variables. Multicollinearity arises when predictor variables exhibit high correlations, potentially leading to unstable coefficient estimates and inflated standard errors in regression analysis. With VIF values within this range, as observed in Table 5.4, it suggests that the predictor variables in the proposed model maintain relative independence from each other, implying a lack of excessive duplication of information or strong linear relationships. This is a favorable scenario as it implies that the estimated coefficients for each predictor variable are likely to remain stable and reliable. In summary, these VIF values indicate low multicollinearity within the regression model, thereby strengthening the validity of this analysis and facilitating more confident interpretations of the relationships between predictor variables and the dependent variable.

### 5.2.6. Comparison Between Direct Effects: Without and With Markers

*Table 5.5 – Comparison Between Direct Effects: Without and With Markers*

| | Without Markers | | | | | With Markers | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Paths** | **Beta** | **Std. Deviation** | **T Statistics** | **P Values** | **CI [2.5%; 97.5%]** | **Beta** | **Std. Deviation** | **T Statistics** | **P Values** | **CI [2.5%; 97.5%]** |
| BC ➔ ExpAI | -0.013 | 0.075 | 0.176 | 0.860 | [-0.155; 0.136] | -0.024 | 0.079 | 0.299 | 0.765 | [-0.173; 0.137] |
| Eng ➔ OW | 0.375 | 0.060 | 6.238 | 0.000 | [0.254; 0.489] | 0.368 | 0.062 | 5.983 | 0.000 | [0.245; 0.484] |
| EnvMind ➔ ExpAI | 0.120 | 0.050 | 2.399 | 0.016 | [0.022; 0.220] | 0.064 | 0.047 | 1.348 | 0.178 | [-0.028; 0.154] |
| Eth ➔ Eng | 0.177 | 0.051 | 3.463 | 0.001 | [0.082; 0.283] | 0.166 | 0.052 | 3.172 | 0.002 | [0.068; 0.273] |
| ExpAI ➔ OW | 0.517 | 0.057 | 9.078 | 0.000 | [0.405; 0.628] | 0.513 | 0.057 | 8.996 | 0.000 | [0.401; 0.625] |
| ExpAI ➔ TOP | 0.566 | 0.049 | 11.614 | 0.000 | [0.466; 0.661] | 0.540 | 0.055 | 9.816 | 0.000 | [0.429; 0.642] |
| OPriv ➔ Eng | 0.313 | 0.063 | 4.958 | 0.000 | [0.189; 0.438] | 0.268 | 0.067 | 4.028 | 0.000 | [0.138; 0.397] |
| OV ➔ ExpAI | 0.739 | 0.067 | 11.020 | 0.000 | [0.601; 0.863] | 0.731 | 0.073 | 9.994 | 0.000 | [0.582; 0.868] |
| TOP ➔ Eng | 0.329 | 0.059 | 5.539 | 0.000 | [0.210; 0.441] | 0.330 | 0.060 | 5.507 | 0.000 | [0.209; 0.444] |
| Eth x TOP ➔ Eng | 0.095 | 0.035 | 2.704 | 0.007 | [0.028; 0.168] | 0.094 | 0.036 | 2.648 | 0.008 | [0.028; 0.169] |
| OPriv x TOP ➔ Eng | 0.107 | 0.042 | 2.522 | 0.012 | [0.021; 0.187] | 0.094 | 0.043 | 2.201 | 0.028 | [0.008; 0.173] |

*Source: Own elaboration based on PLS outputs | BC: Brand Credibility, Eng: Consumer Engagement, EnvMind: Environmental Mindfulness, Eth: Ethics Position, ExpAI: Experience with Artificial Intelligence, OPriv: Overall Online Privacy, OV: Overall Values, OW: Overall Well-being, TOP: Trust in Online Platforms.*

The purpose of Table 5.5 is to compare the direct effects of the proposed models, specifically the model without BL markers (Table 5.6) and the one with BL markers (Appendix D), which were introduced to assess the potential bias through Common Method Bias. The similarity in beta values between the two models suggests low multicollinearity within the regression model, reinforcing the importance of ensuring accuracy and reliability in the analysis, leading to confident interpretations of the relationships between predictor variables and the dependent variable. Minimal differences in estimated coefficients indicate stability and reliability, indicating that the markers have a limited impact on established relationships. These findings are consistent with the low multicollinearity observed in the Collinearity statistics table (Table 5.4).

### 5.2.7. Direct, Specific Indirect and Total Effects

*Table 5.6 – Direct, Specific Indirect and Total Effects: Without Markers*

| Direct Effects - Without Markers | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Paths** | **Beta** | **Std. Deviation** | **T Statistics** | **P Values** | **CI (2.5%)** | **CI (97.5%)** | **VIF** | **Hypothesis** |
| EnvMind ➔ ExpAI | 0.120 | 0.050 | 2.399 | 0.016 | 0.022 | 0.220 | 1.052 | H1: Supported ($p<0.05$) |
| BC ➔ ExpAI | -0.013 | 0.075 | 0.176 | 0.860 | -0.155 | 0.136 | 2.161 | H2: Not Supported |
| OV ➔ ExpAI | 0.739 | 0.067 | 11.020 | 0.000 | 0.601 | 0.863 | 2.226 | H3: Supported ($p<0.001$) |
| ExpAI ➔ TOP | 0.566 | 0.049 | 11.614 | 0.000 | 0.466 | 0.661 | 1.000 | H4: Supported ($p<0.001$) |
| TOP ➔ Eng | 0.329 | 0.059 | 5.539 | 0.000 | 0.210 | 0.441 | 1.533 | H5: ($p<0.001$) |
| ExpAI ➔ OW | 0.517 | 0.057 | 9.078 | 0.000 | 0.405 | 0.628 | 2.164 | H6: Supported ($p<0.001$) |
| Eng ➔ OW | 0.375 | 0.060 | 6.238 | 0.000 | 0.254 | 0.489 | 2.164 | H7: Supported ($p<0.001$) |

| Direct Effects - Without Markers | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Paths** | **Beta** | **Std. Deviation** | **T Statistics** | **P Values** | **CI (2.5%)** | **CI (97.5%)** | **VIF** | **Hypothesis** |
| Eth x TOP ➔ Eng | 0.095 | 0.035 | 2.704 | 0.007 | 0.028 | 0.168 | 1.149 | H8: (p<0.01) |
| OPriv x TOP ➔ Eng | 0.107 | 0.042 | 2.522 | 0.012 | 0.021 | 0.187 | 1.152 | H9: (p<0.05) |
| Eth ➔ Eng | 0.177 | 0.051 | 3.463 | 0.001 | 0.082 | 0.283 | 1.192 | N/A* |
| OPriv ➔ Eng | 0.313 | 0.063 | 4.958 | 0.000 | 0.189 | 0.438 | 1.569 | N/A* |

| Specific Indirect Effects - Without Markers | | | | | | |
|---|---|---|---|---|---|---|
| **Paths** | **Beta** | **Std. Deviation** | **T statistics** | **P values** | **CI (2.5%)** | **CI (97.5%)** |
| BC ➔ ExpAI ➔ OW | -0.007 | 0.039 | 0.175 | 0.861 | -0.081 | 0.071 |
| BC ➔ ExpAI ➔ TOP | -0.007 | 0.043 | 0.175 | 0.861 | -0.084 | 0.082 |
| EnvMind ➔ ExpAI ➔ OW | 0.062 | 0.027 | 2.302 | 0.021 | 0.011 | 0.118 |
| OV ➔ ExpAI ➔ TOP ➔ Eng ➔ OW | 0.052 | 0.015 | 3.443 | 0.001 | 0.026 | 0.084 |
| EnvMind ➔ ExpAI ➔ TOP | 0.068 | 0.028 | 2.430 | 0.015 | 0.013 | 0.125 |
| Eth ➔ Eng ➔ OW | 0.066 | 0.022 | 3.005 | 0.003 | 0.029 | 0.116 |
| OV ➔ ExpAI ➔ OW | 0.382 | 0.057 | 6.706 | 0.000 | 0.272 | 0.499 |
| OV ➔ ExpAI ➔ TOP ➔ Eng | 0.138 | 0.032 | 4.304 | 0.000 | 0.079 | 0.204 |
| OV ➔ ExpAI ➔ TOP | 0.419 | 0.053 | 7.942 | 0.000 | 0.319 | 0.524 |
| OPriv ➔ Eng ➔ OW | 0.117 | 0.030 | 3.859 | 0.000 | 0.063 | 0.182 |
| TOP ➔ Eng ➔ OW | 0.123 | 0.031 | 3.954 | 0.000 | 0.067 | 0.189 |
| Eth x TOP ➔ Eng ➔ OW | 0.036 | 0.014 | 2.512 | 0.012 | 0.011 | 0.066 |
| OPriv x TOP ➔ Eng ➔ OW | 0.040 | 0.017 | 2.305 | 0.021 | 0.007 | 0.075 |
| BC ➔ ExpAI ➔ TOP ➔ Eng | -0.002 | 0.014 | 0.172 | 0.864 | -0.027 | 0.029 |

| Specific Indirect Effects - Without Markers | | | | | | |
|---|---|---|---|---|---|---|
| **Paths** | **Beta** | **Std. Deviation** | **T statistics** | **P values** | **CI (2.5%)** | **CI (97.5%)** |
| Env Mind ➔ ExpAI ➔ TOP ➔ Eng | 0.022 | 0.010 | 2.164 | 0.031 | 0.004 | 0.045 |
| EnvMind ➔ ExpAI ➔ TOP ➔ Eng ➔ OW | 0.008 | 0.004 | 1.971 | 0.049 | 0.001 | 0.018 |
| ExpAI ➔ TOP ➔ Eng ➔ OW | 0.070 | 0.020 | 3.547 | 0.000 | 0.036 | 0.113 |
| ExpAI ➔ TOP ➔ Eng | 0.186 | 0.041 | 4.537 | 0.000 | 0.110 | 0.269 |
| **Total Effects - Without Markers** | | | | | | |
| **Paths** | **Beta** | **Std. Deviation** | **T Statistics** | **P Values** | **CI (2.5%)** | **CI (97.5%)** |
| BC ➔ Eng | -0.002 | 0.014 | 0.172 | 0.864 | -0.027 | 0.029 |
| BC ➔ ExpAI | -0.013 | 0.075 | 0.176 | 0.860 | -0.155 | 0.136 |
| BC ➔ OW | -0.008 | 0.044 | 0.175 | 0.861 | -0.090 | 0.082 |
| BC ➔ TOP | -0.007 | 0.043 | 0.175 | 0.861 | -0.084 | 0.082 |
| Eng ➔ OW | 0.375 | 0.060 | 6.238 | 0.000 | 0.254 | 0.489 |
| EnvMind ➔ Eng | 0.022 | 0.010 | 2.164 | 0.031 | 0.004 | 0.045 |
| EnvMind ➔ ExpAI | 0.120 | 0.050 | 2.399 | 0.016 | 0.022 | 0.220 |
| EnvMind ➔ OW | 0.070 | 0.030 | 2.350 | 0.019 | 0.013 | 0.132 |
| EnvMind ➔ TOP | 0.068 | 0.028 | 2.430 | 0.015 | 0.013 | 0.125 |
| Eth ➔ Eng | 0.177 | 0.051 | 3.463 | 0.001 | 0.082 | 0.283 |
| Eth ➔ OW | 0.066 | 0.022 | 3.005 | 0.003 | 0.029 | 0.116 |
| ExpAI ➔ Eng | 0.186 | 0.041 | 4.537 | 0.000 | 0.110 | 0.269 |
| ExpAI ➔ OW | 0.586 | 0.049 | 12.005 | 0.000 | 0.490 | 0.683 |
| ExpAI ➔ TOP | 0.566 | 0.049 | 11.614 | 0.000 | 0.466 | 0.661 |

| Total Effects - Without Markers | | | | | | |
|---|---|---|---|---|---|---|
| **Paths** | **Beta** | **Std. Deviation** | **T Statistics** | **P Values** | **CI (2.5%)** | **CI (97.5%)** |
| OPriv ➔ Eng | 0.313 | 0.063 | 4.958 | 0.000 | 0.189 | 0.438 |
| OPriv ➔ OW | 0.117 | 0.030 | 3.859 | 0.000 | 0.063 | 0.182 |
| OV ➔ Eng | 0.138 | 0.032 | 4.304 | 0.000 | 0.079 | 0.204 |
| OV ➔ ExpAI | 0.739 | 0.067 | 11.020 | 0.000 | 0.601 | 0.863 |
| OV ➔ OW | 0.433 | 0.056 | 7.798 | 0.000 | 0.325 | 0.545 |
| OV ➔ TOP | 0.419 | 0.053 | 7.942 | 0.000 | 0.319 | 0.524 |
| TOP ➔ Eng | 0.329 | 0.059 | 5.539 | 0.000 | 0.210 | 0.441 |
| TOP ➔ OW | 0.123 | 0.031 | 3.954 | 0.000 | 0.067 | 0.189 |
| Eth x TOP ➔ Eng | 0.095 | 0.035 | 2.704 | 0.007 | 0.028 | 0.168 |
| Eth x TOP ➔ OW | 0.036 | 0.014 | 2.512 | 0.012 | 0.011 | 0.066 |
| OPriv x TOP ➔ Eng | 0.107 | 0.042 | 2.522 | 0.012 | 0.021 | 0.187 |
| OPriv x TOP ➔ OW | 0.040 | 0.017 | 2.305 | 0.021 | 0.007 | 0.075 |

| Mediation Analysis Results | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Paths** | **Beta** | **Std. Deviation** | **T Statistics** | **P Values** | **CI (2.5%)** | **CI (97.5%)** | **Result** |
| ExpAI ➔ TOP ➔ Eng ➔ OW | 0.070 | 0.020 | 3.547 | 0.000 | 0.036 | 0.113 | Partial mediation |

*Source: Own elaboration based on PLS outputs |* ****N/A****: Not applicable as these relationships are not included in the proposed conceptual framework (Figure 3.1). | BC: Brand Credibility, Eng: Consumer Engagement, EnvMind: Environmental Mindfulness, Eth: Ethics Position, ExpAI: Experience with Artificial Intelligence, OPriv: Overall Online Privacy, OV: Overall Values, OW: Overall Well-being, TOP: Trust in Online Platforms.*

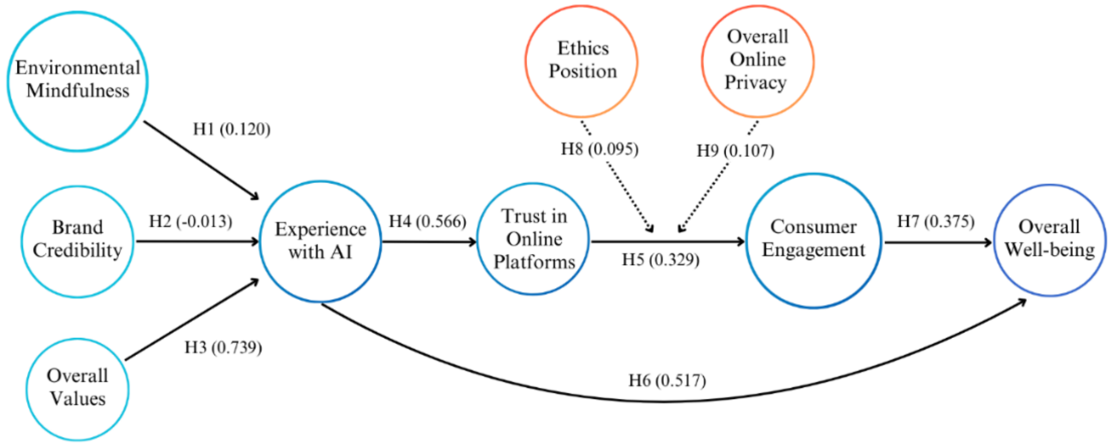
The results of the statistical analysis of the proposed model's direct effects (Table 5.6) reveal that contrary to expectations the relationship between the independent variable BC and the dependent variable ExpAI is not statistically significant. With a p-value of 0.860 exceeding the common significance level of 0.05, we fail to reject the null hypothesis, indicating no meaningful relationship between the predictor and dependent variable. Thus, hypothesis H2 (Brand Credibility [BC] negatively influences Experience with AI [ExpAI].) is rejected or not supported, suggesting that BC-ExpAI may not exert a significant impact within the proposed model.

To evaluate the significance of the other variables, their respective p-values are crucial indicators of their associations with the dependent variable. P-values below 0.05 denote statistically significant relationships (H1 and H9), while those below 0.01 and 0.001 signify heightened and exceptional significance (H3, H4, H5, H6, H7, and H8), respectively. Variables meeting these criteria represent supported hypotheses, contributing significantly to the research objectives. These findings strengthen the credibility of the regression results and bolster confidence in the drawn conclusions.

The variance inflation factor (VIF) values ranging from 1.000 to 2.226 indicate high independence among variables, minimizing concerns about multicollinearity. This enhances the reliability of the regression outcomes and facilitates more confident interpretations of predictor variables' relationships with the dependent variable.

Upon closer examination of the direct effects (Table 5.6), significant relationships emerge between ExpAI and OW, ExpAI and TOP, and TOP and Eng, all with p-values below 0.05 (0.000). This implies partial mediation by the mediators ExpAI and TOP, and a significant moderation of the moderator Eng, indicating a combination of direct and indirect effects in play. However, additional factors may contribute to the overall effect, underscoring the complexity of these relationships. Further analysis of specific indirect effects reveals the role of partial mediators within the proposed model, as seen by the mediation analysis results in Table 16. Paths such as "Eth x TOP → Eng → OW" and "OPriv x TOP → Eng → OW" suggest potential moderation effects, while "ExpAI → TOP → Eng → OW" indicates mediation effects. This intricate interplay underscores the complexity of the model's relationships, emphasizing the importance of considering both direct and indirect pathways in understanding its dynamics.

*Figure 5.1 – PLS Results*




*Source: Author's own elaboration*

The structural model, as seen in Figure 5.1, forms the core of the study and aims to elucidate the interrelations among latent variables and reveal the outcomes of hypothesis tests. This analysis is grounded in the Partial Least Squares (PLS) results presented above (Figure 5.1), followed by the detailed results supporting the conceptual framework.

The structural model delineates two distinct categories of variables: endogenous and exogenous latent constructs. Endogenous variables, including Environmental Mindfulness (EnvMind), Brand Credibility (BC), Overall Values (OV), Experience with AI (ExpAI), Trust in Online Platforms (TOP), Consumer Engagement (Eng), and Overall Well-being (OW), are subject to influence from other constructs through structural model relationships, and thus serve as mediators within the conceptual model. Conversely, exogenous latent constructs such as Ethics Position (Eth) and Overall Online Privacy (OPriv) serve as moderators within the model, exerting influence on the relationships between other variables without direct structural paths.

The beta values derived from PLS calculations offer insights into the strength and direction of relationships within the structural model. Noteworthy beta values include 0.120 for H1, indicating a significant positive effect of Environmental Mindfulness on Experience with AI; -0.013 for H2, suggesting a significant negative effect of Brand Credibility on Experience with AI; and 0.739 for H3, indicating a robust positive relationship between Overall Values and Experience with AI. Other significant beta values include 0.566 for H4, 0.329 for H5, 0.517 for H6, 0.375 for H7, 0.095 for H8, and 0.107 for H9, each highlighting significant relationships within the structural model.

Throughout the analysis, strict criteria are sustained, requiring that all path coefficients exceed 0.2 and exhibit p-values lower than 0.05.

### 5.2.8. F-square

*Table 5.7 – F-square Matrix*

| | BC | Eng | Env Mind | Eth | ExpAI | OPriv | OV | OW | TOP | Eth x TOP | OPriv x TOP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BC | | | | | 0.000 | | | | | | |
| Eng | | | | | | | | 0.210 | | | |
| EnvMind | | | | | 0.033 | | | | | | |
| Eth | | 0.055 | | | | | | | | | |
| ExpAI | | | | | | | | 0.399 | 0.472 | | |
| OPriv | | 0.130 | | | | | | | | | |
| OV | | | | | 0.593 | | | | | | |
| OW | | | | | | | | | | | |
| TOP | | 0.147 | | | | | | | | | |
| Eth x TOP | | 0.022 | | | | | | | | | |
| OPriv x TOP | | 0.025 | | | | | | | | | |

*Source: Own elaboration based on PLS outputs | BC: Brand Credibility, Eng: Consumer Engagement, EnvMind: Environmental Mindfulness, Eth: Ethics Position, ExpAI: Experience with Artificial Intelligence, OPriv: Overall Online Privacy, OV: Overall Values, OW: Overall Well-being, TOP: Trust in Online Platforms.*

In PLS-SEM, the f-square statistic is utilized as a measure of the effect size of latent variables on endogenous constructs denoted as Y, indicating their susceptibility to influence from other variables in the model. It indicates the proportion of variance explained in each endogenous construct by its corresponding latent variable. A comprehensive understanding of these values is crucial for evaluating the strength of relationships within the model.

Following the guidelines outlined by Chin (1998) and Hair et al. (2011), the interpretation of the f-square results from Table 5.7 is conducted. According to Chin, an f-square value below 0.19 signifies a very weak effect, while values falling between 0.19 and 0.33 denote a weak effect. Hair et al. propose that an f-square below 0.25 indicates a very weak relationship, while values between 0.25 and 0.50 represent a weak relationship.

Upon reviewing the obtained results in Table 5.7 based on those guidelines, it is evident that the effects of Brand Credibility on Experience with AI and Environmental Mindfulness on Experience with AI are very weak, with f-square values of 0.000 and 0.033, respectively.

Conversely, the effect of Overall Values on Experience with AI is substantial, with an f-square value of 0.593.

In sum, these f-square values align with the earlier calculated beta values, reinforcing our understanding of the relationships between latent variables and endogenous constructs within the model. This coherence suggests a consistent pattern in the strength of these relationships.

Thus, while certain relationships in the model exhibit weak effects, such as Brand Credibility (BC) and Environmental Mindfulness (EnvMind) on Experience with AI (ExpAI), the substantial effect of Overall Values (OV) on Experience with AI (ExpAI) indicates a robust relationship deserving of further investigation. Overall, the f-square analysis provides invaluable insights into the strength of relationships within the structural model, thereby contributing to the assessment of model fit and theoretical implications.

### 5.2.9. Measurement Model Prediction

*Table 5.8 – Measurement Model Prediction*

| Variables | $Q^2$predict | R-square |
|---|---|---|
| Eng | 0.483 | 0.520 |
| ExpAI | 0.569 | 0.585 |
| OW | 0.604 | 0.691 |
| TOP | 0.400 | 0.321 |

*Source: Own elaboration based on PLS outputs | Eng: Consumer Engagement, ExpAI: Experience with Artificial Intelligence, OW: Overall Well-being, TOP: Trust in Online Platforms.*

Regarding measurement model prediction, Table 5.8 provides valuable insights into the predictive relevance and explanatory power of the variables in the model. The table shows that the variable OW is the strongest predictor and explains a significant amount of variance in the outcome, as evidenced by its highest $Q^2$ predict and R-square values. On the other hand, TOP has the lowest values, suggesting that it has less predictive power and explains less variance in the model. To encapsulate, the measurement model's prediction is generally positive, considering that most of the variables exhibit relatively high $Q^2$ predict and R-square values. Higher values (closer to 1) for these metrics typically suggest a more accurate and reliable prediction of the model. Therefore, the positive values seen in the table suggest that the measurement model is effective in predicting the outcome based on the variables included.

### 5.2.10. Chi-square and Model Fit

*Table 5.9 – Model Fit*

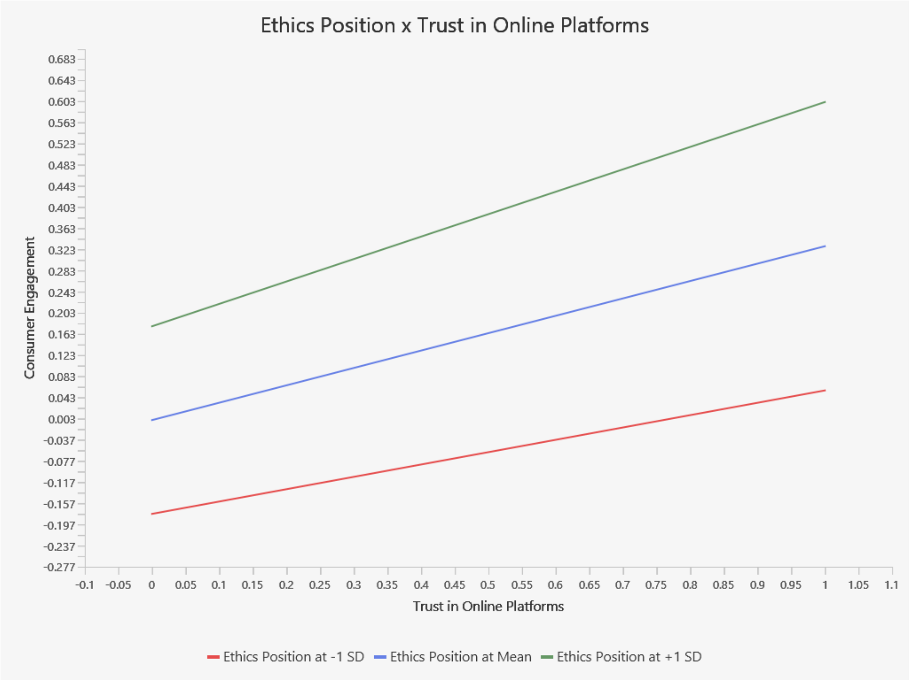
| Model Fit | |
|---|---|
| SRMR | 0.060 |
| Chi-Square | 5221.651 |
| NFI | 0.727 |

*Source: Own elaboration based on PLS outputs*

As analyzed through Table 5.9, the proposed model exhibits a reasonable degree of fit, with the majority of data points falling within the expected range. Additionally, it indicates that, on average, the disparities between the observed and predicted correlations are relatively minor. Nonetheless, upon closer examination, it becomes apparent that the NFI value could be elevated, ideally approaching 1. This implies that there exist potential areas for enhancement within the model.

### 5.2.11. Simple Slope Analysis

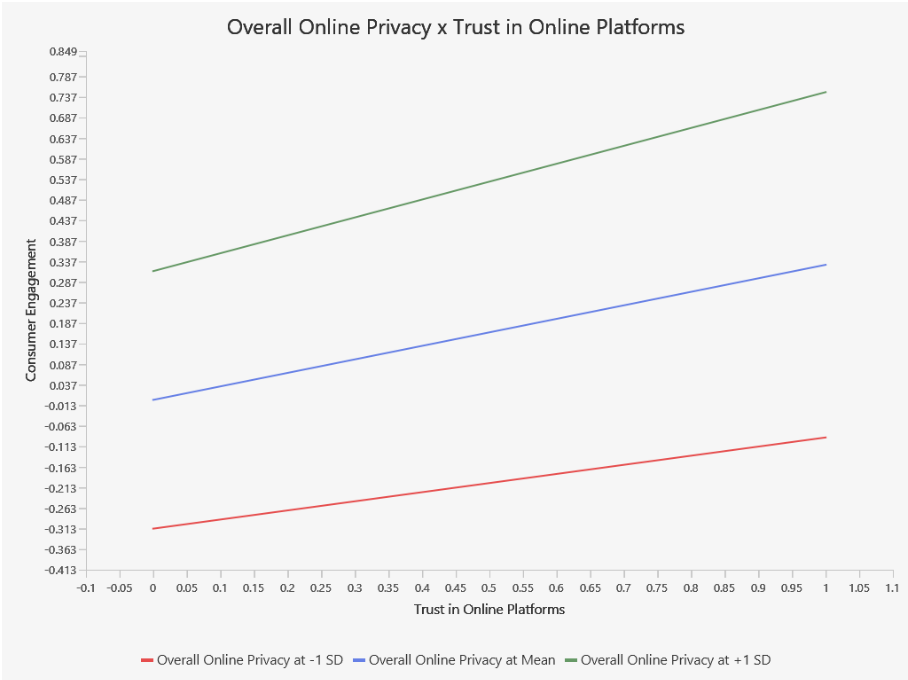
*Figure 5.2 - Simple Slope Plot for "Eth x TOP" Interaction*




*Source: PLS outputs*

In Figure 5.2, three distinct trajectories are observed, each corresponding to different levels of the Ethics Position (Eth) variable concerning the Mean. The plot clearly shows that there is a positive relationship between the Trust in Online Platforms (TOP) variable and the Consumer Engagement (Eng) variable. As TOP increases, so does Eng. Over time, the trajectories diverge, indicating a growing difference between them.

*Figure 5.3 - Simple Slope Plot for "OPriv x TOP" Interaction*




*Source: PLS outputs*

Moving on to Figure 5.3, a similar pattern is discerned, but with trajectories exhibiting a semblance of parallelism, although not entirely parallel upon closer examination. The alignment of trajectories, albeit not strictly parallel, suggests that there is a less pronounced moderation effect of OPriv on the relationship between TOP and Eng compared to Eth.

In conclusion, these observations suggest that OPriv does influence the relationship between TOP and Eng, but its moderation effect appears comparatively weaker than that of Eth.

### 5.3. Discussion

After carefully analyzing the results, evaluating their alignment with the hypotheses outlined in the literature review and conceptual framework is crucial. Thus, this section will specifically focus on validating the anticipated relationships identified in the literature review and highlighting any deviations from the expected outcomes.

The literature review extensively discussed the correlation between Brand Credibility (BC) and Experience with AI (ExpAI), with numerous studies suggesting a positive connection (Chen et al., 2022). However, contrary to expectations, our analysis revealed that the relationship between BC and ExpAI (H2) is not statistically significant. This unexpected result contradicts existing literature, suggesting a necessity for further exploration into the intricate dynamics between brand credibility and AI experiences.

The lack of support for Hypothesis 2 (H2) could be attributed to various factors. One potential explanation is the conflicting consumer perspectives on brand credibility and AI-generated recommendations within the fast fashion industry. While previous research underscores the importance of brand credibility in fostering consumer trust in AI recommendations (Chen et al., 2022), the participants in this study might harbor differing levels of skepticism toward AI technology due to concerns about its accuracy or relevance.

Secondly, consumers may have different experiences with different brands, leading to diverse perceptions of brand credibility. Consumer decision-making in this context is intricate and influenced by factors beyond brand credibility, such as price, convenience, and personal preferences.

Thirdly, the study indicates that consumer ethics and values (OV) play a significant role in shaping perceptions of AI experiences (H3). It is plausible that ethical considerations outweighed brand credibility in this specific context. Consumers who prioritize ethical behavior, sustainability, and transparency may assign less significance to brand credibility when assessing AI recommendations.

Fourthly, the study underscores the importance of Trust in Online Platforms (TOP) as a predictor of consumer engagement (H4 and H5). Even if consumers trust the platform itself regardless of individual brand credibility, they may still engage with AI-powered features. This suggests that trust in the platform's overall functionality and reliability could outweigh brand-specific credibility.

Fifthly, the diverse demographic backgrounds among study participants may also contribute to the lack of support for H2. Differences in demographics might lead to varying responses to brand credibility and AI. For instance, tech-savvy consumers accustomed to AI technology might prioritize its functionality over brand credibility. Similarly, consumers deeply involved in the fast fashion industry might prioritize trends and convenience over brand reputation when considering AI recommendations.

The effectiveness of AI implementation within the studied fast fashion context is another crucial consideration. If AI recommendations are not perceived as useful or accurate by consumers, brand credibility might not significantly impact their experiences. Additionally, recent marketing strategies might have overshadowed brand credibility. Brands heavily promoting AI features could have shifted consumer focus towards AI functionality rather than brand credibility.

Consumer behavior is known to be intricate and influenced by a complex interplay of variables. The relationship between brand credibility, trust, and ethical considerations might be more nuanced and multifaceted than initially thought. The study might not have captured all the variables at play, such as past experiences with AI in fast fashion or peer influences, which could have influenced consumer perceptions.

Overall, our analysis confirmed Hypotheses 1, 3, 4, and 5, which align with prior research findings and contribute to the coherence of the conceptual model. The empirical evidence supports the robustness of the theoretical framework and the validity of our research approach.

Hypothesis 1 (H1) proposed a positive association between Environmental Mindfulness (EnvMind) and Experience with AI (ExpAI). This aligns with recent research indicating that consumers are increasingly conscious of environmental impacts and seek sustainable practices within the fashion industry (Santos et al., 2021; Rudolph et al., 2023). Companies demonstrating a commitment to environmental sustainability through AI-powered initiatives can enhance consumer experiences and foster positive brand perceptions.

Hypothesis 3 (H3) posited that Overall Values (OV) positively influence Experience with AI (ExpAI), consistent with recent studies highlighting the significant role of consumer ethics and values in shaping perceptions of AI experiences (Garcia-Ortega et al., 2023). This finding underscores the importance of ethical considerations in consumer decision-making processes, particularly in evaluating AI-driven initiatives that align with personal beliefs and values.

In addition, Hypotheses 4 and 5 (H4 and H5) suggested positive relationships between Experience with AI (ExpAI) and Trust in Online Platforms (TOP), as well as between Trust in Online Platforms (TOP) and Consumer Engagement (Eng). These hypotheses were supported by empirical evidence, emphasizing the significance of trust and positive AI experiences in driving consumer engagement within the fast fashion industry (Verma et al., 2021).

In conclusion, our analysis validated the majority of the anticipated associations detailed in the literature review. Nevertheless, the absence of backing for Hypothesis 2 (H2) underscores the intricate nature of consumer perceptions and decision-making mechanisms in the context of AI-driven marketing. By situating our findings within the current body of literature and pinpointing potential explanations for discrepancies, this discourse provides valuable perspectives for forthcoming research and theoretical progressions in the domain.

To gain a deeper understanding of the implications of these findings, a thorough examination of the descriptive statistics results was conducted for each of the ten constructs analyzed in the study. Firstly, the analysis of environmental mindfulness (EnvMind), specifically the dimensions of environmental awareness (EAw) and environmental concern (EC), within the fast fashion industry provided fascinating insights into respondents' attitudes towards sustainability. In general, respondents demonstrated a moderate level of agreement, indicating a widespread awareness and concern for environmental issues. Particularly noteworthy were statements related to preserving natural resources, which received high average ratings, suggesting a strong consensus among participants regarding the importance of sustainable practices. However, the analysis also revealed variability in responses, especially concerning the perceived impact of legislation and the commercial advantage of environmental policies. This variability, as indicated by higher standard deviations, underscores the nuanced nature of environmental consciousness among consumers in the fast fashion sector.

Moreover, the examination of brand credibility (BC) within the fast fashion context revealed a nuanced landscape of trust and skepticism among the surveyed respondents. While there was an overall moderate agreement regarding brand credibility, with respondents expressing trust in brands delivering on promises, there were notable variations in perceptions. Confidence in the believability of service claims exhibited significant variability, indicating differing levels of trust among participants. This divergence in responses suggests that while certain aspects of brand credibility may resonate positively with consumers, others may be met with more skepticism, highlighting the importance of fostering transparent and authentic brand-consumer relationships.

The analysis of overall values (OV), encompassing the dimensions of perceived quality value (PQV), perceived social value (PSV), perceived emotional value (PEV), and personal values (V), within the context of AI integration in the fast fashion industry, has unveiled a complex interplay between personal beliefs and technological influence. Our survey respondents generally concurred on the significance of AI recommendations aligning with personal values, indicating a preference for personalized and socially conscious suggestions. Nonetheless, there exists variability in perceptions, particularly concerning the reliability of AI recommendations and their impact on social perception. This diversity suggests that while consumers value the alignment of AI suggestions with their values, they also harbor reservations about the authenticity and societal implications of AI-driven decision-making processes.

An investigation into consumer experience with artificial intelligence (ExpAI) technology in the fast fashion sector has revealed a spectrum of attitudes and perceptions. Although respondents showed a lack of consensus regarding their experience with AI, certain aspects garnered moderate agreement. The acceptance of encountering AI-related practices during shopping received relatively positive ratings, implying a certain level of familiarity and comfort with AI integration. However, there was less agreement on the significant influence of AI on decisions, indicating varying levels of trust and reliance on AI technology among consumers. This disparity underscores the necessity for further exploration into the factors shaping consumer perceptions of AI in the fast fashion domain.

The analysis of trust in online platforms (TOP) within the fast fashion industry has unveiled a nuanced perspective among respondents. While there was a moderate level of agreement regarding trust in online platforms for purchases, there were notable variations in perceptions. Comfort in using online platforms received relatively positive ratings, signifying a general trust in the online shopping experience. However, there was less agreement on online platforms prioritizing consumer interests, reflecting differing levels of trust and skepticism among participants. This variability underscores the significance of transparency and consumer-centric practices in fostering trust and loyalty in online platforms.

Upon examining the ethical position (Eth) in consumer decision-making, a comprehensive analysis revealed a complex interplay of principles and values among the respondents. The study found a consensus on specific ethical principles, such as the avoidance of harm and adherence to moral decision-making criteria. However, there existed variability in perceptions regarding the overall importance of ethical principles, indicating differing levels of emphasis placed on ethics in decision-making processes. This variability underscores the necessity for brands and retailers to navigate the ethical landscape with caution, aligning with consumer values while acknowledging diverse perspectives on ethical priorities.

A thorough investigation into overall online privacy (OPriv) in the fast fashion industry, specifically focusing on the dimensions of online privacy concern (PCon) and online privacy policies (PPol), unveiled a nuanced perspective of consumers on data protection and personal information security. While there was a moderate level of agreement regarding online privacy concerns, notable variations in perceptions were evident. The study revealed a significant level of concern about personal information sharing, indicating a general apprehension towards data privacy practices. However, there was less agreement on consumers having options regarding data usage, reflecting differing levels of awareness and control over online privacy settings. This variability underscores the critical importance of transparency and user empowerment in addressing consumer concerns about online privacy.

Exploring consumer engagement (Eng) with fast fashion trends revealed diverse attitudes and perceptions among the respondents. While there was a low level of agreement regarding consumer engagement, certain aspects elicited moderate agreement. The study indicated a relatively positive reception of enthusiasm about trends, suggesting a degree of interest and involvement in industry developments. However, there was less agreement on receiving personal compliments about the industry's success, indicating varying levels of emotional connection and brand affinity among participants. This diversity underscores the multifaceted nature of consumer engagement and the importance of tailored strategies to foster meaningful connections with consumers.

Further research into perceptions of overall well-being (OW), specifically focusing on the dimensions of Psychological Well-being (PW) and Consumer Well-being (CW) concerning fashion decisions, uncovered a nuanced understanding of the intersection between personal expression and psychological fulfillment. The study revealed a moderate level of agreement regarding individual freedom in fashion choices, alongside notable variations in perceptions. The findings indicated a general appreciation for valuing freedom in fashion, emphasizing self-expression and autonomy in style decisions. However, there was less agreement on fashion contributing to stability and satisfaction, reflecting differing perspectives on the emotional and psychological impact of fashion consumption. This variability highlights the need for holistic approaches to well-being in the fashion industry, encompassing both individual empowerment and collective societal impact.

Lastly, the investigation into consumer preferences for blue color markers (BL) in fashion choices yielded intriguing insights. Respondents generally exhibited a moderate level of agreement regarding their preferences for the color blue, with nuanced differences in perceptions. While the affinity for the blue color received positive ratings overall, there was less consensus on the preference for blue footwear, indicating diverse inclinations among participants. This variability underscores the subjective nature of fashion preferences and emphasizes the importance of offering a range of options to cater to individual tastes and preferences.

Subsequently, the results of the partial least squares structural equation modeling (PLS-SEM) and bootstrapping calculations conducted in SmartPLS were explored to elucidate the dynamics and relationships between constructs, thereby shedding light on the underlying patterns in consumer behavior within the fast fashion industry.

The analysis of direct effects unveiled significant relationships between specific variables, such as Experience with AI (ExpAI) and Overall Well-being (OW), Trust in Online Platforms (TOP), and Consumer Engagement (Eng). These findings substantiate specific hypotheses and significantly contribute to comprehending the dynamics of the proposed model. This underscores the notable influence of variables such as Experience with AI on consumer well-being and engagement with online platforms, underscoring the significance of these factors in shaping consumer behavior in the context of fast fashion.

The variance inflation factor (VIF) values below 3.33 indicate minimal multicollinearity among predictor variables in the regression model. This favorable scenario implies stable and reliable coefficient estimates, reinforcing the validity of the analysis and the interpretation of relationships between predictor variables and the dependent variable. By ensuring low multicollinearity, the reliability of the regression outcomes is enhanced, facilitating more confident interpretations of the relationships between predictor variables and the dependent variable, thus bolstering the overall robustness of the analysis.

The comprehensive analysis of construct reliability, convergent validity, and discriminant validity provides compelling evidence of the robustness and accuracy of the measures utilized in the study, thereby bolstering assurance in the study's findings. This meticulous scrutiny ensures that the constructs in the model effectively encapsulate the intended concepts and remain distinct from each other. Consequently, the reliability and validity of the measurements are established, thereby reinforcing the credibility of the study's results, and supporting sound interpretations within the theoretical framework.

The assessment of measurement model prediction and model fit (Tables 5.8 and 5.9) indicates a reasonable level of fit and predictive relevance, with variables exhibiting relatively high $Q^2$ predict and R-square values, thereby enhancing certainty in the model's predictive accuracy. These outcomes suggest that the proposed model adequately elucidates the variance in the outcome variables and possesses the predictive capacity to anticipate consumer behavior within the fast fashion context. This underscores the model's efficacy in capturing the intricacies of consumer decision-making processes and offers valuable insights for industry practitioners and policymakers.

The f-square analysis yields invaluable insights into the strength of relationships within the structural model, contributing to the evaluation of model fit and theoretical implications. By examining the effect sizes of latent variables on endogenous constructs, the f-square analysis highlights the relative importance of different factors in influencing consumer behavior. This nuanced understanding serves to refine the theoretical framework and inform future research directions, ultimately enriching scholarly discourse in the field of consumer behavior and fashion marketing.

The inclusion of blue color markers (BL) in the model aimed to assess the potential bias introduced by common method bias (CMB), specifically in self-reported questionnaire data. Despite initial concerns regarding common method bias, the comparison between the model without BL markers and the one with BL markers revealed minimal differences in estimated coefficients. This suggests that the markers had limited impact on established relationships, indicating low potential for common method bias in the data, which is highly favorable for the integrity and scope of this study.

The similarity in beta values across the models highlights the stability and robustness of the analysis, even with the inclusion of BL markers. This emphasis on precision and consistency in the analysis serves to bolster assurance in the interpretations of the relationships between predictor variables and the dependent variable. These findings are in line with the low multicollinearity observed in collinearity statistics, further reinforcing the credibility of the analysis and enabling more confident interpretations of the results.

The HTMT values, which indicate satisfactory discriminant validity, suggest that the constructs within the proposed measurement model effectively differentiate between different elements and demonstrate acceptable discriminant validity. By establishing the distinctiveness of the constructs and their measurement of different underlying concepts, these findings alleviate concerns about potential common method bias influencing the relationships between variables in the model.

Overall, the incorporation of BL markers and the comprehensive investigation of collinearity statistics and discriminant validity offer assurance regarding the strength and soundness of the analysis. By addressing potential sources of bias, such as common method bias, the study enhances the credibility of its findings and facilitates more reliable interpretations of the relationships between variables. These results contribute to the methodological rigor of the study and enhance the credibility of the study's outcomes, ultimately enriching the scholarly discussion on consumer behavior within the fast fashion industry.

Taking it all together, the current study distinguishes itself from existing literature through its focused investigation into AI-driven marketing strategies within the fast fashion industry. It provides a detailed understanding of the distinctive challenges and opportunities in this dynamic sector. While prior research often explores AI applications across retail sectors broadly, this study delves specifically into fast fashion, recognizing its distinctive characteristics such as rapid trends, evolving consumer expectations, and sustainability imperatives. Moreover, this research sets itself apart by meticulously examining moderating factors like online privacy, ethics position, and trust in online platforms, uncovering the intricate mechanisms that influence consumer responses to AI technology in fast fashion. By providing detailed explanations for both supported and unsupported hypotheses, this study contributes significantly to theoretical advancements in AI-driven marketing strategies, enriching scholarly discourse with multifaceted insights into consumer perceptions and behaviors. Notably, this dissertation's unwavering focus on sustainability and ethics within the fast fashion paradigm sets it apart, offering pragmatic implications for industry practitioners and policymakers. In essence, this master's dissertation makes a substantial scholarly contribution through its industry-specific inquiry, comprehensive moderation analysis, elaborated hypothesis explanations, and emphasis on sustainability and ethics, thereby informing industry practices, fostering academic dialogue, and promoting conscientious consumer behaviors amidst the proliferation of AI technologies in contemporary marketing contexts.

### 5.4. Theoretical Contributions

This dissertation presents a comprehensive synthesis of foundational theories in consumer behavior, marketing, and technology within the fast fashion industry, thereby providing innovative insights and expanding existing theoretical frameworks. By integrating diverse theoretical perspectives, the study advances scholarly understanding, offering practical implications for industry stakeholders.

The incorporation of AI into fast fashion marketing strategies represents a significant theoretical advancement, drawing upon established theories of consumer behavior and technological innovation. Building upon well-established frameworks, such as consumer engagement theory (Rosado-Pinto & Loureiro, 2020) and the Fear of Missing Out (FOMO) concept (Bläse et al., 2024), this research extends theoretical boundaries to encompass the multifaceted implications of AI-driven marketing in the fast fashion context.

This study contributes to theoretical advancements by adopting a multidisciplinary approach, incorporating insights from ethical retailing practices (Rudolph et al., 2023) and the role of emotional intelligence in service experiences (Prentice & Nguyen, 2020). This interdisciplinary perspective enriches theoretical foundations by providing a holistic understanding of consumer behavior and marketing dynamics within the fast fashion industry.

The research addresses gaps and limitations in existing literature, contributing to theoretical knowledge by elucidating previously unexplored aspects of consumer engagement with AI (Chen et al., 2022) and the intersection of ethical considerations and privacy in consumer decision-making (Stringer et al., 2020). Through empirical investigation and theoretical analysis, the study identifies key gaps in the literature and offers nuanced insights into consumer behavior and marketing strategies in the fast fashion sector.

In sum, this dissertation significantly enhances theoretical knowledge in the interdisciplinary field of consumer behavior, marketing, and technology within the fast fashion industry by synthesizing diverse theoretical perspectives, adopting a multidisciplinary approach, and addressing gaps in the literature. Through its theoretical contributions, this study not only advances scholarly understanding but also provides practical insights that can inform industry practices and decision-making processes.

## 5.5. Managerial Implications

In examining the dynamic landscape of fast fashion, this study delves into essential insights and provides practical guidance for stakeholders in the industry. Departing from traditional academic discourse, the distilled findings presented here offer actionable strategies and pragmatic considerations for managerial decision-making.

A key takeaway pertains to the implementation of consumer-centric strategies. Success in the field of fast fashion depends on the comprehension and anticipation of consumer needs and preferences. Through the adoption of AI-driven personalization and the utilization of data analytics, brands can design customized experiences that resonate with their target audience. By investing in technologies that enable real-time engagement and dynamic adaptation to evolving consumer behaviors, brands can cultivate loyalty and boost their competitiveness in the market.

Above all, this study underscores the critical importance of embracing ethical and sustainable practices. In the wake of heightened consumer awareness surrounding ethical and environmental concerns, sustainability has transitioned from being an option to a necessity for fashion brands. The integration of ethical considerations into supply chain management, product development, and marketing strategies is essential. Brands that prioritize transparency, ethical sourcing, and environmental stewardship not only meet regulatory requirements but also appeal to socially and environmentally conscious consumers, thereby enhancing brand reputation and long-term viability. Additionally, embracing sustainability can yield economic benefits for fashion brands. Research indicates that consumers are increasingly willing to pay a premium for products sourced ethically and environmentally friendly. By aligning with sustainability initiatives, fashion brands can tap into a growing market of conscientious consumers, expand their customer base, and enhance profitability.

The focal point of this discussion revolves around the imperative to target socially and environmentally conscious consumers, as well as the equally significant task of promoting environmental and social awareness across broader consumer segments. The fast fashion industry's considerable environmental footprint necessitates concerted efforts to mitigate its detrimental effects on the environment. Fostering awareness and advocating for sustainable practices across all consumer segments can catalyze widespread change and mobilize collective action toward a more sustainable future. Embracing the promotion of environmental and social consciousness is aligned with the urgent need for the fast fashion industry to address its environmental challenges and contribute positively to global sustainability efforts.

Indeed, strategic partnerships and collaborations emerge as potent strategies for navigating the multifaceted challenges facing the fast fashion industry. Recognizing the complexity of these challenges, collaboration across sectors and disciplines becomes essential. By forming alliances with technology firms, sustainability experts, and advocacy groups, fashion brands can combine resources, share best practices, and drive collective action toward common goals. Strategic partnerships enable access to specialized expertise, innovative solutions, and new market opportunities, positioning brands for sustainable growth and enduring success.

Finally, this dissertation underscores the significance of continuous innovation and adaptation in the fast fashion industry. In a rapidly evolving marketplace characterized by technological disruptions and shifting consumer preferences, agility and adaptability are paramount. Fashion brands must cultivate a culture of innovation, embracing experimentation, iteration, and risk-taking. Embracing emerging technologies, exploring new business models, and anticipating future trends will enable brands to stay ahead of the curve and remain relevant in an increasingly competitive landscape.

Finally, this dissertation highlights the transformative potential of consumer-centric, ethical, and collaborative approaches in navigating the complexities of the fast fashion industry. By heeding these insights and embracing strategic innovation, fashion brands can not only thrive in today's dynamic market but also contribute positively to society, the environment, and global sustainability efforts.

## Chapter 6 – Conclusions and Recommendations

This dissertation extensively examines the profound impact of AI-driven personalization on consumer behavior and sustainability within the fast fashion industry. By scrutinizing the complex intersections of technological innovation, consumer preferences, privacy considerations, and ethical imperatives, the study provides valuable insights into the contemporary dynamics of fast fashion marketing.

The research concludes that AI-driven personalization significantly influences consumer purchase behavior in the fast fashion industry. It is observed that personalized recommendations and targeted marketing strategies enhance consumer engagement and increase purchase intentions. However, this influence is subject to moderation by privacy concerns and ethical considerations, highlighting the essential need for transparent and secure data practices. Furthermore, the study acknowledges that emerging trends and technological advancements, particularly in AI, are reshaping consumer engagement and market dynamics. AI technologies are found to enable brands to deliver more relevant and timely content, thereby fostering deeper consumer connections. Nonetheless, the rapid evolution of these advancements necessitates continuous adaptation and innovation by industry stakeholders.

The dissertation also highlights the critical role of sustainable practices and ethical initiatives in mitigating the environmental footprint of fast fashion. Indeed, consumers increasingly value sustainability and are influenced by brands' ethical commitments. The integration of these practices into marketing strategies is shown not only to enhance brand reputation but also to promote responsible consumption.

Drawing from these findings, the study offers several recommendations. First and foremost, fast fashion brands are advised to prioritize transparency in data collection and usage to build consumer trust. Implementing robust data security measures and effectively communicating these efforts to consumers can mitigate privacy concerns and foster a sense of trust and loyalty. Second, it is suggested that brands should leverage AI technologies to develop and promote sustainable products. AI is found to be capable of optimizing supply chain processes, reducing waste, and creating personalized marketing campaigns that highlight sustainability efforts, thus appealing to environmentally conscious consumers. Third, given the rapid evolution of AI technologies, fast fashion brands are urged to continuously innovate and adapt their strategies. Staying abreast of technological advancements and consumer trends is deemed essential for brands to maintain relevance and competitiveness in the market. Lastly, ethical considerations are emphasized as paramount in guiding AI implementation. Brands are advised to ensure that their use of AI aligns with ethical standards, respects consumer privacy, and avoids exploitative practices. The integration of ethical AI practices is posited as a means to enhance brand integrity and consumer trust.

### 6.1. Limitations

However, the study acknowledges several limitations. Data collection was confined to specific geographic regions and demographic groups, potentially impacting the generalizability of the findings. Future research should include more diverse samples to provide a more comprehensive perspective. Additionally, the focus on AI-driven personalization may have overlooked other significant factors influencing consumer behavior. Future studies should explore additional drivers such as social media influence, economic conditions, and brand reputation. The research was conducted within a specific timeframe and may not capture long-term trends. Therefore, longitudinal studies are recommended to understand the sustained impact of AI and evolving consumer preferences. Moreover, reliance on self-reported data introduces potential biases, and future research could benefit from experimental designs to measure actual consumer reactions and behaviors. Lastly, while ethical and privacy considerations were addressed theoretically and through surveys, real-world applications and consumer reactions to AI-driven personalization were not experimentally tested, requiring further research in practical settings.

### 6.2. Further Research Suggestions

To further elaborate on the findings of this dissertation, future research should aim to include more diverse and representative samples from various regions and demographic groups. This will help in understanding the varying impacts of AI-driven personalization. Longitudinal studies can provide insights into how consumer behavior and perceptions of AI-driven personalization change over time, capturing long-term trends and sustained impacts.

Future studies should also consider additional factors influencing consumer behavior, such as social media, influencer marketing, and economic conditions, for a more comprehensive understanding. Employing experimental research designs could test real-world applications of AI-driven personalization and measure actual consumer reactions, providing concrete evidence of effectiveness and reception.

Further research is needed to explore the practical implications of ethical and privacy considerations in AI-driven personalization, investigating how different approaches impact consumer trust and engagement. As AI technology continues to evolve, future research should focus on innovative uses of AI in promoting sustainability, such as optimizing supply chain processes and developing sustainable products.

Comparing the impact of AI-driven personalization in fast fashion with other industries can provide broader insights and identify best practices, offering valuable lessons for diverse market contexts.

By addressing these limitations and pursuing these future research avenues, scholars can build upon the findings of this dissertation to further understand and improve the interplay between AI-driven personalization, consumer behavior, and sustainability in the fast fashion industry.

## 7. Bibliographical References


Atik, D., & Ozdamar Ertekin, Z. (2023). The restless desire for the new versus sustainability: The pressing need for social marketing in the fashion industry. *Journal of Social Marketing, 13*(1), 1–19. https://doi.org/10.1108/JSOCM-02-2022-0036

Baek, T. H., & King, K. W. (2011). Exploring the consequences of brand credibility in services. *Journal of Services Marketing, 25*(4), 260–272. https://doi.org/10.1108/08876041111143096

Bastos Rudolph, L. T., Bassi Suter, M., & Barakat, S. R. (2023). The emergence of a new business approach in the fashion and apparel industry: The ethical retailer. *Journal of Macromarketing, 43*(3), 367–383. https://doi.org/10.1177/02761467231180456

Bläse, R., Filser, M., Kraus, S., Puumalainen, K., & Moog, P. (2024). Non-sustainable buying behavior: How the fear of missing out drives purchase intentions in the fast fashion industry. *Business Strategy and the Environment, 33*(2), 626-641. https://doi.org/10.1002/bse.3509

Bouman, T., van der Werff, E., Perlaviciute, G., & Steg, L. (2021). Environmental values and identities at the personal and group level. *Current Opinion in Behavioral Sciences, 42,* 47–53. https://doi.org/10.1016/j.cobeha.2021.02.022

Budd, R. J., & Spencer, C. P. (1985). Exploring the role of personal normative beliefs in the theory of reasoned action: The problem of discriminating between alternative path models. *European Journal of Social Psychology, 15*(3), 299–313. https://doi.org/10.1002/ejsp.2420150305

Centobelli, P., Abbate, S., Nadeem, S. P., & Garza-Reyes, J. A. (2022). Slowing the fast fashion industry: An all-round perspective. *Current Opinion in Green and Sustainable Chemistry, 38*, 100684 https://doi.org/10.1016/j.cogsc.2022.100684

Chandra, S., Verma, S., Lim, W. M., Kumar, S., & Donthu, N. (2022). Personalization in personalized marketing: Trends and ways forward. *Psychology and Marketing, 39*(8), 1529–1562. https://doi.org/10.1002/mar.21670

Chen, H., Chan-Olmsted, S., Kim, J., & Mayor Sanabria, I. (2021). Consumers' perception on artificial intelligence applications in marketing communication. *Qualitative Market Research, 25*(1), 125–142. https://doi.org/10.1108/QMR-03-2021-0040

Chin, P. N., Isa, S. M., & Alodin, Y. (2020). The impact of endorser and brand credibility on consumers' purchase intention: The mediating effect of attitude towards brand and brand credibility. *Journal of Marketing Communications, 26*(8), 896–912. https://doi.org/10.1080/13527266.2019.1604561

Cloarec, J. (2022). Privacy controls as an information source to reduce data poisoning in artificial intelligence-powered personalization. *Journal of Business Research, 152*, 144–153. https://doi.org/10.1016/j.jbusres.2022.07.045

Du, S., & Sen, S. (2023). AI through a CSR lens: Consumer issues and public policy. *Journal of Public Policy and Marketing*, *42*(4), 351–353. https://doi.org/10.1177/07439156231186573

European Commission. (2023, June 20). Regulatory framework proposal on artificial intelligence. European Commission. https://ec.europa.eu/newsroom/dae/document.cfm?doc_id=76672

Fisher, G. (2022). The future of AI in business. *Business Insights*. https://www.businessinsights.com/future-of-ai

Gadenne, D. L., Kennedy, J., & McKeiver, C. (2008). An empirical study of environmental awareness and practices in SMEs. *Journal of Business Ethics, 84*(1), 45–63. https://doi.org/10.1007/s10551-008-9672-9

Garcia-Ortega, B., Galan-Cubillo, J., Llorens-Montes, F. J., & de-Miguel-Molina, B. (2023). Sufficient consumption as a missing link toward sustainability: The case of fast fashion. *Journal of Cleaner Production*, *399*. https://doi.org/10.1016/j.jclepro.2023.136678

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice, 19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Henkens, B., Verleye, K., & Larivière, B. (2021). The smarter, the better?! Customer well-being, engagement, and perceptions in smart service systems. *International Journal of Research in Marketing, 38*(2), 425–447. https://doi.org/10.1016/j.ijresmar.2020.09.006

Hong, W., & Thong, J. Y. L. (2013). Internet privacy concerns: An integrated conceptualization and four empirical studies. *MIS Quarterly: Management Information Systems, 37*(1), 275–298. https://doi.org/10.25300/MISQ/2013/37.1.12

Kahle, L. R. (1983). *Social values and social change: Adaptation to life in America*. Praeger.

Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review, 61*(4), 135–155. https://doi.org/10.1177/0008125619859317

Lee, D. J., Sirgy, M. J., Larsen, V., & Wright, N. D. (2002). Developing a subjective measure of consumer well-being. *Journal of Macromarketing, 22*(2), 158–169. https://doi.org/10.1177/0276146702238219

Long, X., & Nasiry, J. (2022). Sustainability in the fast fashion industry. *SSRN*. https://ssrn.com/abstract=3486502

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research, 13*(3), 334–359. https://doi.org/10.1287/isre.13.3.334.81

Minton, A. P., & Rose, R. L. (1997). The effects of environmental concern on environmentally friendly consumer behavior: An exploratory study. *Journal of Business Research, 40*(1), 37-48. https://doi.org/10.1016/S0148-2963(96)00209-8

Mrad, M., Majdalani, J., Cui, C. C., & El Khansa, Z. (2020). Brand addiction in the contexts of luxury and fast-fashion brands. *Journal of Retailing and Consumer Services, 55*, 102089. https://doi.org/10.1016/j.jretconser.2020.102089

Muncy, J. A., & Vitell, S. J. (1992). Consumer ethics: An investigation of the ethical beliefs of the final consumer. *Journal of Business Research, 24*(4), 297-311. https://doi.org/10.1016/0148-2963(92)90036-B

Musikanski, L., Rakova, B., Bradbury, J., Phillips, R., & Manson, M. (2020). Artificial intelligence and community well-being: A proposal for an emerging area of research. *International Journal of Community Well-Being, 3*(1), 39–55. https://doi.org/10.1007/s42413-019-00054-6

Parker-Strak, R., Barnes, L., Studd, R., & Doyle, S. (2020). Disruptive product development for online fast fashion retailers. *Journal of Fashion Marketing and Management*, *24*(3), 517–532. https://doi.org/10.1108/JFMM-08-2019-0170

Pataranutaporn, P., Danry, V., Leong, J., Punpongsanon, P., Novy, D., Maes, P., & Sra, M. (2021). AI-generated characters for supporting personalized learning and well-being. *Nature Machine Intelligence, 3*(12), 1013–1022. https://doi.org/10.1038/s42256-021-00417-9

Peters, G., Li, M., & Lenzen, M. (2021). The need to decelerate fast fashion in a hot climate: A global sustainability perspective on the garment industry. *Journal of Cleaner Production, 295*, 126390. https://doi.org/10.1016/j.jclepro.2021.126390

Pitofsky, R., Azcuenaga, M. L., Anthony, S. F., Thompson, M. W., Landesberg, M. K., Blumenthal, D. M., & Pascoe, G. A. (1998). *Privacy online: A report to Congress*. Federal Trade Commission. https://www.ftc.gov/reports/privacy-online-report-congress

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Prentice, C., & Nguyen, M. (2020). Engaging and retaining customers with AI and employee service. *Journal of Retailing and Consumer Services, 56*, 102186. https://doi.org/10.1016/j.jretconser.2020.102186

Roozen, I., & Raedts, M. (2020). The power of negative publicity on the fast fashion industry. *Journal of Global Fashion Marketing*, *11*(4), 380–396. https://doi.org/10.1080/20932685.2020.1798802

Rosado-Pinto, F., & Loureiro, S. M. C. (2020). The growing complexity of customer engagement: A systematic review. *EuroMed Journal of Business*, *15*(2), 167-203. https://doi.org/10.1108/EMJB-10-2019-0126

Salem, S. F., & Salem, S. O. (2021). Effects of social media marketing and selected marketing constructs on stages of brand loyalty. *Global Business Review, 22*(3), 650–673. https://doi.org/10.1177/0972150919830863

Santos, C., Gabriel, G., Amaral, J., Montevechi, J., & Queiroz, J. (2021). Decision-making in a fast fashion company in the Industry 4.0 era - a Digital Twin proposal to support operational planning. *The International Journal of Advanced Manufacturing Technology, 116*(5-6), 1-14. https://doi.org/10.1007/s00170-021-07728-2

Servera-Francés, D., & Piqueras-Tomás, L. (2019). The effects of corporate social responsibility on consumer loyalty through consumer perceived value. *Economic Research-Ekonomska Istraživanja, 32*(1), 66–84. https://doi.org/10.1080/1331677X.2018.1547202

Singh, S., & Singh, W. (2023). AI-based personality prediction for human well-being from text data: A systematic review. *Multimedia Tools and Applications*. https://doi.org/10.1007/s11042-023-17282-w

So, K. K. F., King, C., Sparks, B. A., & Wang, Y. (2014). The role of customer engagement in building consumer loyalty to tourism brands. *Journal of Travel Research, 55*(1), 64–78. https://doi.org/10.1177/0047287514541008

Stringer, T., Mortimer, G., & Payne, A. R. (2020). Do ethical concerns and personal values influence the purchase intention of fast-fashion clothing? *Journal of Fashion Marketing and Management, 24*(1), 99–120. https://doi.org/10.1108/JFMM-01-2019-0011

Takyar, A. (2023). AI use cases & applications across major industries. *LeewayHertz*. https://www.leewayhertz.com/ai-use-cases-and-applications/

Umair Manzoor, S., Ahmad Baig, S., Hashim, M., & Sami, A. (2020). Impact of social media marketing on consumer's purchase intentions: The mediating role of customer trust. *International Journal of Entrepreneurial Research, 3*(2), 41–48. https://doi.org/10.31580/ijer.v3i2.1386

Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. *International Journal of Information Management Data Insights, 1*(1), 100002. https://doi.org/10.1016/j.jjimei.2020.100002

Walsh, G., Shiu, E., & Hassan, L. M. (2014). Replicating, validating, and reducing the length of the consumer perceived value scale. *Journal of Business Research*, *67*(3), 260–267. https://doi.org/10.1016/j.jbusres.2013.05.012

Williams, L. J., Hartman, N., & Cavazotte, F. (2010). Method variance and marker variables: A review and comprehensive CFA marker technique. *Organizational Research Methods*, *13*(3), 477–514. https://doi.org/10.1177/1094428110366036

Wolford, B. (2023). Everything you need to know about GDPR. *GDPR.eu*. https://gdpr.eu/what-is-gdpr/

# 8. Appendixes

## Appendix A: Questionnaire

**Dissertation on AI-Driven Personalization in Fast Fashion and its Implications for Consumer Behavior and Sustainability.**

By Joana André

£1,50 • £9,00/hr | 10 mins | 50 places

This Master's Dissertation in Marketing, conducted at ISCTE Business School, explores diverse aspects through this questionnaire, including environmental awareness, AI-driven personalization in fast fashion, psychological well-being related to fashion, experience with AI, online privacy, trust in fast fashion platforms, and more. The primary objective is to **understand the implications of AI personalization in fast fashion for consumer behavior and sustainability.**

Participants will only be asked to share their perspectives/opinions on various aspects, with no "right" or "wrong" answers, which will significantly contribute to this academic investigation. So, we advise you to answer it as honestly as you can.

**Participation Details:**

- **MUST be a resident in the USA!**
- **MUST have had at least 1 experience with Artificial Intelligence (AI)!**

**Other Details:**

- All data will be collectively analyzed and kept confidential exclusively for academic purposes, ensuring participant anonymity.
- No sensitive information is required.
- Participants are only obligated to provide these personal details: age, gender, and education.
- This questionnaire does not involve downloading software or requiring specific equipment.
- Completion of all questions is mandatory to ensure the effectiveness of this investigation.
- The expected completion time is approximately 10 minutes.

**Thank you in advance for your interest in this research!**

Devices you can use to take this study:

Desktop Mobile Tablet

Open study link in a new window

This questionnaire was developed as part of a Master's Dissertation in Marketing at ISCTE Business School, from Instituto Universitário de Lisboa. Your participation in this study is crucial, as your insights will significantly enhance the academic investigation on the theme: "AI-Driven Personalization in Fast Fashion and its Implications for Consumer Behavior and Sustainability."

All data will be collectively analyzed and kept confidential exclusively for academic purposes, ensuring participant anonymity.

Please be aware that there are no 'right' or 'wrong' responses, as this study aims to explore your perceptions on the topic. However, completing all questions is mandatory. Rest assured, we've designed this questionnaire to take only approximately 10 minutes of your time.

Thank you in advance for your valuable collaboration!

*Please enter your Prolific ID:

*Q1 - Age. What is your age?

*Q2 - Gender. Which gender do you identify yourself with?

- Male
- Female
- Other
- Prefer not to say

*Q3 - Education. What is the highest degree or level of school you have completed?

- Less than high school
- High school degree or equivalent (e.g. GED)
- College
- Bachelor degree
- Master degree
- Doctorate degree (PhD.D) or higher
- Other (you can specify below)

*Q4 - Residence. Are you currently residing in the United States of America?

◯ Yes ◯ No

*Q5 - AI. Have you ever utilized an algorithm or device incorporating Artificial Intelligence (AI)? (e.g., chatbots like ChatGPT, Buoy Health, and Poe)

◯ Yes ◯ No

*Q6 - EA. Please rate your level of agreement with the following statements regarding your environmental awareness, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| I am uncertain about the environmental impact of companies in the fast fashion sector. | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| I perceive limited benefits for companies in the fast fashion sector from environmental initiatives. | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| Currently, having an environmental policy does not seem commercially advantageous for companies in the fast fashion sector. | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| It is challenging to identify what constitutes 'best practice' in environmental performance for companies in the fast fashion sector. | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| The impact of legislation on operations in the fast fashion sector is not always clear to me. | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |

*Q7 - EC. Please rate your level of agreement with the following statements regarding your environmental concern, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| The fast fashion industry should take more measures to conserve scarce natural resources. | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| Preserving natural resources is essential, even if it means sacrificing some fast fashion products. | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| I wish there were more governmental efforts to control environmental pollution caused by the fast fashion industry. | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| Air and water pollution from the fast fashion industry receive more attention than they deserve. | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| I feel upset when considering the harm pollution caused by the fast fashion industry to plant and animal life. | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |
| The government should allocate more funds to support conservation and environmental programs related to the fast fashion industry. | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Consumers should consider the environmental impact of fast fashion products they buy. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Consumers should be willing to pay higher prices for fast fashion products that are environmentally friendly. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Taxing non-recyclable containers in the fast fashion industry could help reduce waste. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| The government should financially support research on technology for recycling waste products in the fast fashion industry. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Fast fashion manufacturers should be obligated to use recycled materials whenever feasible. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Commercial advertising of fast fashion products should disclose the environmental drawbacks. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Fast fashion products causing environmental harm should be subject to additional taxes. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Public schools should mandate courses covering environmental and conservation issues related to the fast fashion industry. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I feel upset about the ways the fast fashion industry harms the environment. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Environmental issues related to the fast fashion industry are overemphasized and do not concern me. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*Q8 - PQV. Please rate your level of agreement with the following statements according to your perceived quality value on AI recommendations in fast fashion, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| I trust AI suggestions for consistently high-quality fast fashion items. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I perceive AI-guided fast fashion products as well-made and reliable. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I believe AI recommendations ensure acceptable quality in fast fashion choices. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I expect AI recommendations to avoid suggesting low-quality or short-lived fast fashion items. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I trust AI recommendations for fast fashion items with durability and lasting quality. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I believe AI-driven suggestions in fast fashion prioritize products with enduring quality and reliability. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*Q9 - PSV. Please rate your level of agreement with the following statements according to your perceived social value on AI recommendations in fast fashion, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| I believe AI suggestions in fast fashion would enhance my social acceptance. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I perceive AI-guided recommendations in fast fashion as positively influencing social perception. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I trust AI recommendations to help me create positive impressions on people and gain social approval. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I expect AI suggestions in fast fashion to lead to socially approved items. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*Q10 - PEV. Please rate your level of agreement with the following statements according to your perceived emotional value on AI recommendations in fast fashion, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| I believe AI suggestions in fast fashion would offer items I genuinely enjoy. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I trust AI-guided recommendations in fast fashion to make me want to use suggested items. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I expect AI recommendations in fast fashion to suggest items I feel comfortable using. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I believe AI-driven suggestions in fast fashion would offer items that please me and feel good to use. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I trust that AI recommendations in fast fashion would provide me with items that evoke positive emotions and connections. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*Q11 - PW . Please rate your level of agreement with the following statements regarding your psychological well-being related to fashion, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| My fashion choices contribute to a sense of stability and satisfaction in my life. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I feel empowered to voice my concerns or preferences in my fashion choices, even within my social circles or family. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I feel in charge of my fashion choices, following my preferences rather than external influences (e.g., trends). | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I feel I have a significant role in determining my fashion choices and what suits me within my social/family context. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I value the freedom to make my own fashion decisions based on personal preferences and individual style. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*Q12 - Experience AI. Please rate your level of agreement with the following statements regarding your experience with AI, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| I am familiar with AI technology's role in shaping fast fashion recommendations. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I have had prior experiences with AI-driven technologies influencing my fast fashion choices. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I feel positive about the use of AI in suggesting fashion options. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| AI significantly influences my decisions related to fast fashion. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I have actively engaged with AI-driven technology for fashion-related suggestions. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I perceive AI interactions as a helpful tool for fashion recommendations. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I can easily differentiate between AI-based fashion recommendations and other sources. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I have concerns about the use of AI in shaping fast fashion recommendations. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I have encountered AI-related practices (e.g., personalized recommendations, chatbots) while shopping for fast fashion items. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| AI-driven practices have influenced my decisions when purchasing fast fashion items. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I have used AI-driven technology to explore or evaluate fashion brands. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I perceive differences in fashion brands when accessed through AI-driven technology compared to traditional media. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| AI technology influences my perception of fashion brands. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| My perception of fashion recommendations differs based on AI-driven technology. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*Q13 - OPC . Please rate your level of agreement with the following statements regarding your online privacy concern, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| It usually bothers me when fast fashion websites ask for my personal information. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| When fast fashion websites request my personal information, I sometimes think twice before providing it. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I am concerned that fast fashion websites are collecting too much personal information about me. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| I am concerned that when I give personal information to a fast fashion website for a specific reason, the website might use the information for other purposes. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I am concerned that fast fashion websites might sell my personal information in their computer database to other companies. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I am concerned that fast fashion websites might share my personal information with other companies without my authorization. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I am concerned that fast fashion websites do not take enough steps to ensure the accuracy of my personal information in their files. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I am concerned that fast fashion websites do not have adequate procedures to correct errors in my personal information. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I am concerned that fast fashion websites do not devote enough time and effort to verify the accuracy of my personal information in their databases. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I am concerned that databases containing my personal information in the fast fashion industry are not adequately protected from unauthorized access. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I am concerned that fast fashion websites do not devote enough time and effort to prevent unauthorized access to my personal information. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I am concerned that fast fashion websites do not take enough steps to ensure that unauthorized people cannot access my personal information in their computers. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| It usually bothers me when I lack control over the personal information I provide to fast fashion websites. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| It usually bothers me when I lack control or autonomy over decisions about how my personal information is collected, used, and shared by fast fashion websites. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I am concerned when control is lost or unwillingly reduced as a result of a marketing transaction with fast fashion websites. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| It usually bothers me when the online privacy policy of fast fashion websites does not have a clear and conspicuous disclosure. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| It usually bothers me when I am not aware or knowledgeable about how my personal information will be used by fast fashion websites. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| It usually bothers me when fast fashion websites seeking my information online do not disclose the way the data are collected, processed, and used. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*Q14 - OPP. Please rate your level of agreement with the following statements regarding online privacy policies in fast fashion, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Fast fashion websites disclose their information practices before collecting personal information from consumers. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Consumers are given options regarding whether personal information collected from them by fast fashion websites may be used for purposes beyond those for which the information was provided. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Consumers are given options regarding how personal information collected from them by fast fashion websites may be used for purposes beyond those for which the information was provided. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Consumers are able to view the accuracy and completeness of data collected about them by fast fashion websites. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Consumers are able to contest the accuracy and completeness of data collected about them by fast fashion websites. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Fast fashion websites take reasonable steps to ensure that information collected from consumers is accurate. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Fast fashion websites take reasonable steps to ensure that information collected from consumers is secure from unauthorized use. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*Q15 - TOP. Please rate your level of agreement with the following statements regarding your trust in online platforms of fast fashion, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| I feel I can trust most online platforms where I shop for fast fashion items. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I feel comfortable using online platforms to purchase fast fashion products. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I believe most online platforms are truthful in their dealings with me. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I believe most online platforms in the fast fashion industry act with my best interests in mind. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*Q16 - PV. Here is a list of things people look for or want out of life. Please rate the importance of each value in your life on a scale from 1 (= Not Important) to 7 (= Extremely Important).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Excitement. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Warm relationships with others. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Being well respected. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Security. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Sense of belonging. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Fun and enjoyment in life. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Self-fulfillment. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| A sense of accomplishment. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Self-respect. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*Q17 - BC. Please rate your level of agreement with the following statements regarding your credibility in fast fashion brands, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| My favorite brand(s) of fast fashion deliver(s) what they promise. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Service claims from my favorite brand(s) of fast fashion are believable. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Over time, my experiences with my favorite brand(s) of fast fashion have led me to expect it/them to keep its/their promises, no more and no less. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| My favorite brand(s) of fast fashion is/are committed to delivering on its/their claim, no more and no less. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| My favorite brand(s) of fast fashion has a name/have names I can trust. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| My favorite brand(s) of fast fashion can deliver what it/they promise(s). | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*Q18 - CE-Engage. Please rate your level of agreement with the following statements regarding your engagement with fast fashion, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| I am passionate about the fast fashion industry. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I am enthusiastic about trends in the fast fashion industry. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Anything related to fast fashion grabs my attention. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I am immersed in my interaction with trends in the fast fashion industry. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| In general, I thoroughly enjoy exchanging ideas with other fast fashion enthusiasts. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| When interacting with fast fashion trends, it is difficult to detach myself. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| When someone praises the fast fashion industry, it feels like a personal compliment. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I am proud of the success of the fast fashion industry. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*Q19 - CW. Please rate your level of agreement with the following statements regarding how AI personalization in fast fashion affects your well-being, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| The quality of AI-driven recommendations significantly influences my satisfaction with fast fashion purchases. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| AI-influenced pricing alignment with my fast fashion preferences and ethical considerations is crucial for my overall well-being in my fashion choices. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| AI customization plays a key role in impacting my choices and contributing to my well-being regarding sustainability preferences in fast fashion. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| AI-driven customer service experiences have a substantial effect on my satisfaction with fast fashion, positively contributing to my overall well-being. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| My satisfaction with AI-influenced fashion items is closely tied to considerations of sustainability and ethical dimensions, contributing to my overall sense of well-being. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| AI-driven personalization significantly impacts my satisfaction with fast fashion, contributing to my overall sense of well-being. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Sustainability considerations have a notable impact on my satisfaction when disposing of AI-recommended items, contributing to my overall well-being. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| AI integration significantly influences store ambiance during my fast fashion shopping, contributing to my overall well-being. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| AI's influence on the availability of desired fast fashion items significantly affects my choices, contributing to my overall well-being. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| My satisfaction with AI's impact on adopting more sustainable and ethical fashion styles is crucial for my overall well-being. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*Q20 - EP. Please rate your level of agreement with the following statements regarding your ethics, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| A person should make certain that their actions never intentionally harm another even to a small degree. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Risks to another should never be tolerated, irrespective of how small the risks might be. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| The existence of potential harm to others is always wrong, irrespective of the benefits to be gained. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| One should never psychologically or physically harm another. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| One should not perform an action which might in any way threaten the dignity and welfare of another individual. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| If an action could harm an innocent other, then it should not be done. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Deciding whether or not to perform an act by balancing the positive consequences of the act against the negative consequences of the act is immoral. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| The dignity and welfare of people should be the most important concern in any society. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| It is never necessary to sacrifice the welfare of others. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Moral actions are those which closely match ideals of the most "perfect" action. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| There are no ethical principles that are so important that they should be a part of any code of ethics. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| What is ethical varies from one situation and society to another. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Moral standards should be seen as being individualistic; what one person considers to be moral may be judged to be immoral by another person. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Different types of moralities cannot be compared as to "rightness." | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| What is ethical for everyone can never be resolved since what is moral or immoral is up to the individual. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Moral standards are simply personal rules which indicate how a person should behave, and are not to be applied in making judgments of others. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Ethical considerations in interpersonal relations are so complex that individuals should be allowed to formulate their own individual codes. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Rigidly codifying an ethical position that prevents certain types of actions stands in the way of better human relations and adjustment. No rule concerning lying can be formulated; whether a lie is permissible or not permissible totally depends upon the situation. Whether a lie is judged to be moral or immoral depends upon the circumstances surrounding the action. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

*Q21 - Blue. Please rate your level of agreement with the following statements regarding your opinion on the color blue, on a scale from 1 (= Strongly Disagree) to 7 (= Strongly Agree).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| I like the color blue. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Blue makes me feel relaxed. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I often choose blue clothing items. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I prefer wearing blue footwear over other colored footwear. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

We thank you for your time spent taking this survey.

Your response has been recorded.

**Prolific code**: C1A4IKNX

## Appendix B. Measurement Scales of the Sociodemographic Characteristics

| Category | Scale | Labels |
|---|---|---|
| **Gender** | 0-3 | 0=Male, 1=Female, 2=Other, 3=Prefer not to say |
| **Education** | 0-6 | 0=Less than high school,<br>1=High school degree or equivalent (e.g. GED), 2=College, 3=Bachelor degree, 4=Master degree, 5=Doctorate degree (PhD.D) or higher, 6=Other |
| **Education: Specified "Other"** | 0-2 | 0=Technical/ technical college, 1=Some college, 2=Associate's degree |

*Source: Own elaboration*

## Appendix C. Descriptive Statistics

### Sample Frequency Across Gender

| | Gender | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| **Valid** | Male | 77 | 34.5 | 34.5 | 34.5 |
| | Female | 138 | 61.9 | 61.9 | 96.4 |
| | Other | 4 | 1.8 | 1.8 | 98.2 |
| | Prefer not to say | 4 | 1.8 | 1.8 | 100 |
| | **Total** | 223 | 100 | 100 | |
| **Missing** | 0 | | | | |

*Source: Own elaboration based on SPSS outputs*

### Sample Frequency Across Age Groups

| | Age Group | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| **Valid** | 18-24 | 35 | 15.7 | 15.7 | 15.7 |
| | 25-34 | 73 | 32.7 | 32.7 | 48.4 |
| | 35-44 | 32 | 14.3 | 14.3 | 62.8 |
| | 45-54 | 35 | 15.7 | 15.7 | 78.5 |
| | 55-64 | 25 | 11.2 | 11.2 | 89.7 |
| | 65 or older | 23 | 10.3 | 10.3 | 100 |
| | **Total** | 223 | 100 | 100 | |
| **Missing** | 0 | | | | |

*Source: Own elaboration based on SPSS outputs*

### Sample Frequency Across Highest Education Levels

| | Level of Education | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| **Valid** | Less than high school | 0 | 0 | 0 | 0 |
| | High school degree or equivalent (e.g. GED) | 41 | 18.4 | 18.4 | 18.4 |
| | College | 19 | 8.5 | 8.5 | 26.9 |
| | Bachelor degree | 96 | 43 | 43 | 70 |
| | Master degree | 50 | 22.4 | 22.4 | 92.4 |
| | Doctorate degree (PhD.D) or higher | 11 | 4.9 | 4.9 | 97.3 |
| | Other | 6 | 2.7 | 2.7 | 100 |
| | **Total** | 223 | 100 | 100 | |
| **Missing** | 0 | | | | |

*Source: Own elaboration based on SPSS outputs*

**Sample Frequency Across the Answers on “Other” in Highest Education Levels**

| | Other Specific Level of Education | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| **Valid** | Technical college | 2 | 33.3 | 33.3 | 33.3 |
| | Some college | 3 | 50 | 50 | 83.3 |
| | Associate’s degree | 1 | 16.7 | 16.7 | 100 |
| | **Total** | 6 | 100 | 100 | |
| **Missing** | 0 | | | | |

*Source: Own elaboration based on SPSS outputs*

**Sample’s Sociodemographic Characteristics**

| | Age | Gender | Education | Education: Responses to “Other” |
|---|---|---|---|---|
| **Minimum** | 18-24 | Male | High school degree or equivalent (e.g. GED) | Technical/technical college |
| **Maximum** | 65 or older | Prefer not to say | Other | Associate’s degree |
| **Mean** | 35-44 | - | - | - |
| **Median** | 35-44 | Female | Bachelor degree | Some college |
| **Mode** | 25-34 | Female | Bachelor degree | Some college |
| **Std. Deviation** | 1.580 | 0.592 | 1.220 | 0.752 |

*Source: Own elaboration based on SPSS outputs*

### Descriptive Statistics of the Constructs

In the first step of analyzing data, it's crucial to conduct a descriptive statistical examination of the variables present in the conceptual framework (Chapter 3). This involves calculating the mean and standard deviation for each variable. To do this, a new variable was generated for each survey question, assisting in computing means associated with specific constructs. The means were calculated using SPSS software, which provided a comprehensive understanding of the data distribution and variability.

Therefore, a descriptive statistical analysis was performed for the variables outlined in the conceptual framework. The mean and standard deviation of the variables' items are presented first. Then, the mean of each construct was derived by calculating the mean of the means associated with the respective variable. This process was facilitated by SPSS software to ensure accuracy and reliability in computing descriptive statistics. The results were presented in a tabular format, detailing the values obtained through SPSS and PLS, thus enhancing the clarity and comprehensiveness of the analysis.

**Environmental Mindfulness (EnvMind)**

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| **Environmental Awareness (EAw)** | | | |
| EAw1: I am uncertain about the environmental impact of companies in the fast fashion sector. | 4.32 | 1.851 | 0.437 |
| EAw2: I perceive limited benefits for companies in the fast fashion sector from environmental initiatives. | 4.35 | 1.604 | 0.388 |
| EAw3: Currently, having an environmental policy does not seem commercially advantageous for companies in the fast fashion sector. | 4.08 | 1.738 | 0.464 |
| EAw4: It is challenging to identify what constitutes 'best practice' in environmental performance for companies in the fast fashion sector. | 4.30 | 1.674 | 0.528 |
| EAw5: The impact of legislation on operations in the fast fashion sector is not always clear to me. | 4.92 | 1.527 | 0.254 |
| **Environmental Concerns (EC)** | | | |
| EC1: The fast fashion industry should take more measures to conserve scarce natural resources. | 5.94 | 1.145 | -0.207 |
| EC2: Preserving natural resources is essential, even if it means sacrificing some fast fashion products. | 5.98 | 1.210 | -0.255 |
| EC3: I wish there were more governmental efforts to control environmental pollution caused by the fast fashion industry. | 5.85 | 1.302 | -0.181 |
| EC4: Air and water pollution from the fast fashion industry receive more attention than they deserve. | 3.34 | 1.924 | 0.719 |
| EC5: I feel upset when considering the harm pollution caused by the fast fashion industry to plant and animal life. | 5.26 | 1.572 | -0.083 |
| EC6: The government should allocate more funds to support conservation and environmental programs | 5.50 | 1.359 | 0.018 |

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| related to the fast fashion industry. | | | |
| **Environmental Concerns (EC)** | | | |
| EC7: Consumers should consider the environmental impact of fast fashion products they buy. | 5.73 | 1.343 | -0.089 |
| EC8: Consumers should be willing to pay higher prices for fast fashion products that are environmentally friendly. | 5 | 1.544 | 0.384 |
| EC9: Taxing non-recyclable containers in the fast fashion industry could help reduce waste. | 5.13 | 1.400 | 0.274 |
| EC10: The government should financially support research on technology for recycling waste products in the fast fashion industry. | 5.40 | 1.442 | 0.178 |
| EC11: Fast fashion manufacturers should be obligated to use recycled materials whenever feasible. | 5.78 | 1.289 | 0.040 |
| EC12: Commercial advertising of fast fashion products should disclose the environmental drawbacks. | 5.51 | 1.411 | -0.044 |
| EC13: Fast fashion products causing environmental harm should be subject to additional taxes. | 5.57 | 1.431 | 0.052 |
| EC14: Public schools should mandate courses covering environmental and conservation issues related to the fast fashion industry. | 4.85 | 1.733 | 0.344 |
| EC15: I feel upset about the ways the fast fashion industry harms the environment. | 5.24 | 1.532 | -0.084 |
| EC16: Environmental issues related to the fast fashion industry are overemphasized and do not concern me. | 2.98 | 1.968 | 0.660 |
| **Construct: Environmental Mindfulness (EnvMind)** | 5 | 1.739 | |

*Source: Own elaboration based on SPSS and PLS outputs*

The variable Environmental Mindfulness (EnvMind) incorporates 21 items, which are classified into two dimensions: Environmental Awareness (EAw) with five items, and Environmental Concerns (EC) with 16 items, as shown above. Among these items, the statements "EAw5: The impact of legislation on operations in the fast fashion sector is not always clear to me" and "EC2: Preserving natural resources is essential, even if it means sacrificing some fast fashion products" received the highest average ratings of 4.92 and 5.98, respectively. On the other hand, the statements "EAw3: Currently, having an environmental policy does not seem commercially advantageous for companies in the fast fashion sector" and "EC16: Environmental issues related to the fast fashion industry are overemphasized and do not concern me" received the lowest agreement rates, with means of 4.08 and 2.98, respectively. Notably, the items "EAw1: I am uncertain about the environmental impact of companies in the fast fashion sector" and "EC16: Environmental issues related to the fast fashion industry are overemphasized and do not concern me" showed the highest levels of variability in responses, as indicated by the Standard Deviations of 1.851 and 1.968. In contrast, "EAw5: The impact of legislation on operations in the fast fashion sector is not always clear to me" and "EC1: The fast fashion industry should take more measures to conserve scarce natural resources" showed the lowest Standard Deviation values, with 1.527 and 1.145, respectively, implying **greater uniformity in respondents' answers.** Therefore, the overall construct yielded an average value of 5 and a Standard Deviation of 1.739, indicating that the respondents had a **moderate level of agreement** and a **moderate degree of dispersion** around the average.

**Brand Credibility (BC)**

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| BC1: My favorite brand(s) of fast fashion deliver(s) what they promise. | 4.48 | 1.500 | 0.876 |
| BC2: Service claims from my favorite brand(s) of fast fashion are believable. | 4.42 | 1.498 | 0.904 |
| BC3: Over time, my experiences with my favorite brand(s) of fast fashion have led me to expect it/them to keep its/their promises, no more and no less. | 4.46 | 1.512 | 0.892 |
| BC4: My favorite brand(s) of fast fashion is/are committed to delivering on its/their claim, no more and no less. | 4.47 | 1.494 | 0.872 |
| BC5: My favorite brand(s) of fast fashion has a name/have names I can trust. | 4.56 | 1.581 | 0.889 |
| BC6: My favorite brand(s) of fast fashion can deliver what it/they promise(s). | 4.69 | 1.452 | 0.915 |
| **Construct: Brand Credibility (BC)** | 4.51 | 1.506 | |

*Source: Own elaboration based on SPSS and PLS outputs*

The variable Brand Credibility (BC) is composed of six items listed above. The item with the highest average value of 4.69 is "BC6: My favorite brand(s) of fast fashion can deliver what it/they promise(s).". On the other hand, the item "BC2: Service claims from my favorite brand(s) of fast fashion are believable" has the lowest agreement rate with a mean of 4.42. The item "BC5: My favorite brand(s) of fast fashion has a name/have names I can trust" has the highest level of variability in responses, as indicated by the Standard Deviations of 1.581. In contrast, "BC6: My favorite brand(s) of fast fashion can deliver what it/they promise(s)" has the lowest Standard Deviation value (1.452), implying **moderate uniformity in respondents' answers.** Therefore, the overall construct has an average value of 4.51 and a Standard Deviation of 1.506, indicating a **moderate level of agreement** and a **moderate degree of dispersion** around the average.

**Overall Values (OV)**

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| **Perceived Quality Values (PQV)** | | | |
| PQV1: I trust AI suggestions for consistently high-quality fast fashion items. | 3.89 | 1.716 | 0.864 |
| PQV2: I perceive AI-guided fast fashion products as well-made and reliable. | 3.76 | 1.741 | 0.873 |
| PQV3: I believe AI recommendations ensure acceptable quality in fast fashion choices. | 3.85 | 1.701 | 0.862 |
| PQV4: I expect AI recommendations to avoid suggesting low-quality or short-lived fast fashion items. | 3.88 | 1.827 | 0.785 |
| PQV5: I trust AI recommendations for fast fashion items with durability and lasting quality. | 3.72 | 1.840 | 0.857 |
| PQV6: I believe AI-driven suggestions in fast fashion prioritize products with enduring quality and reliability. | 3.68 | 1.824 | 0.862 |
| PSV1: I believe AI suggestions in fast fashion would enhance my social acceptance. | 3.48 | 1.874 | 0.805 |
| PSV2: I perceive AI-guided recommendations in fast | 3.79 | 1.784 | 0.830 |

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| fashion as positively influencing social perception. | | | |
| **Perceived Social Values (PSV)** | | | |
| PSV3: I trust AI recommendations to help me create positive impressions on people and gain social approval. | 3.61 | 1.893 | 0.820 |
| PSV4: I expect AI suggestions in fast fashion to lead to socially approved items. | 4.09 | 1.804 | 0.770 |
| **Perceived Emotional Values (PEV)** | | | |
| PEV1: I believe AI suggestions in fast fashion would offer items I genuinely enjoy. | 4.43 | 1.502 | 0.839 |
| PEV2: I trust AI-guided recommendations in fast fashion to make me want to use suggested items. | 4.16 | 1.655 | 0.872 |
| PEV3: I expect AI recommendations in fast fashion to suggest items I feel comfortable using. | 4.36 | 1.553 | 0.826 |
| PEV4: I believe AI-driven suggestions in fast fashion would offer items that please me and feel good to use. | 4.30 | 1.587 | 0.847 |
| PEV5: I trust that AI recommendations in fast fashion would provide me with items that evoke positive emotions and connections. | 4.17 | 1.642 | 0.851 |
| **Personal Values (V)** | | | |
| V1: Excitement. | 5.36 | 1.240 | 0.329 |
| V2: Warm relationships with others. | 6.22 | 0.965 | 0.058 |
| V3: Being well respected. | 5.63 | 1.325 | 0.242 |
| V4: Security. | 6.27 | 0.949 | 0.018 |
| V5: Sense of belonging. | 5.82 | 1.181 | 0.206 |
| V6: Fun and enjoyment in life. | 6.15 | 0.970 | 0.068 |
| V7: Self-fulfillment. | 6.24 | 1.095 | 0.159 |
| V8: A sense of accomplishment. | 6.07 | 1.080 | 0.242 |
| V9: Self-respect. | 6.32 | 0.964 | 0.114 |
| **Construct: Overall Values (OV)** | 4.72 | 1.844 | |

*Source: Own elaboration based on SPSS and PLS outputs*

The Overall Values (OV) variable consists of twenty-four items, which are divided into four dimensions: Perceived Quality Values (PQV) with six items, Perceived Social Values (PSV) with four items, Perceived Emotional Values (PEV) with five items, and Personal Values (V) with nine items, as shown above. The highest average values were recorded by the items

"PQV1: I trust AI suggestions for consistently high-quality fast fashion items.", "PSV4: I expect AI suggestions in fast fashion to lead to socially approved items.", "PEV1: I believe AI suggestions in fast fashion would offer items I genuinely enjoy.", and "V9: Self-respect.", with scores of 3.89, 4.09, 4.43, and 6.32 respectively. On the other hand, the lowest agreement rate was recorded by the items "PQV6: I believe AI-driven suggestions in fast fashion prioritize products with enduring quality and reliability.", "PSV1: I believe AI suggestions in fast fashion would enhance my social acceptance.", "PEV2: I trust AI-guided recommendations in fast fashion to make me want to use suggested items.", and "V1: Excitement.", with scores of 3.68, 3.48, 4.16, and 5.36 respectively. The items "PQV5: I trust AI recommendations for fast fashion items with durability and lasting quality.", "PSV3: I trust AI recommendations to help me create positive impressions on people and gain social approval.", "PEV2: I trust AI-guided recommendations in fast fashion to make me want to use suggested items.", and "V3: Being well respected." showed the highest variability in responses, with the standard deviations being 1.840, 1.893, 1.655, and 1.325 respectively. Conversely, "PQV3: I believe AI recommendations ensure acceptable quality in fast fashion choices.", "PSV2: I perceive AI-guided recommendations in fast fashion as positively influencing social perception.", "PEV1: I believe AI suggestions in fast fashion would offer items I genuinely enjoy.", and "V4: Security." showed the lowest standard deviation values, with 1.701, 1.784, 1.502, and 0.949 respectively, implying **greater uniformity in responses** from the participants. The aggregate construct yielded an average value of 4.72, with a standard deviation of 1.844, indicating that the respondents had a **moderate level of agreement** and a **moderate degree of dispersion** around the average.

### Experience with Artificial Intelligence (ExpAI)

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| ExpAI1: I am familiar with AI technology's role in shaping fast fashion recommendations. | 3.97 | 1.849 | 0.826 |
| ExpAI2: I have had prior experiences with AI-driven technologies influencing my fast fashion choices. | 3.97 | 1.850 | 0.856 |
| ExpAI3: I feel positive about the use of AI in suggesting fashion options. | 4.18 | 1.629 | 0.764 |
| ExpAI4: AI significantly influences my decisions related to fast fashion. | 3.43 | 1.899 | 0.851 |
| ExpAI5: I have actively engaged with AI-driven | 3.66 | 1.917 | 0.863 |

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| technology for fashion-related suggestions. | | | |
| ExpAI6: I perceive AI interactions as a helpful tool for fashion recommendations. | 4.25 | 1.657 | 0.733 |
| ExpAI7: I can easily differentiate between AI-based fashion recommendations and other sources. | 3.94 | 1.841 | 0.684 |
| ExpAI8: I have concerns about the use of AI in shaping fast fashion recommendations. | 4.04 | 1.802 | 0.386 |
| ExpAI9: I have encountered AI-related practices (e.g., personalized recommendations, chatbots) while shopping for fast fashion items. | 4.60 | 1.886 | 0.679 |
| ExpAI10: AI-driven practices have influenced my decisions when purchasing fast fashion items. | 3.75 | 1.828 | 0.844 |
| ExpAI11: I have used AI-driven technology to explore or evaluate fashion brands. | 3.80 | 1.936 | 0.834 |
| ExpAI12: I perceive differences in fashion brands when accessed through AI-driven technology compared to traditional media. | 3.88 | 1.759 | 0.807 |
| ExpAI13: AI technology influences my perception of fashion brands. | 3.62 | 1.766 | 0.832 |
| ExpAI14: My perception of fashion recommendations differs based on AI-driven technology. | 3.70 | 1.785 | 0.720 |
| **Construct: Experience with AI** | 3.91 | 1.835 | |

*Source: Own elaboration based on SPSS and PLS outputs*

The variable Experience with AI (ExpAI) contains fourteen items, detailed above. Among these, the item "ExpAI9: I have encountered AI-related practices (e.g., personalized recommendations, chatbots) while shopping for fast fashion items" has the highest average value of 4.60. On the other hand, the item "ExpAI4: AI significantly influences my decisions related to fast fashion" has the lowest agreement rate, with a mean of 3.43. Interestingly, the item "ExpAI11: I have used AI-driven technology to explore or evaluate fashion brands" displays the highest levels of variability in responses, with a Standard Deviation of 1.936. Conversely, "ExpAI3: I feel positive about the use of AI in suggesting fashion options" shows the lowest Standard Deviation value (1.629), indicating **moderate uniformity in respondents' answers.** Therefore, the composite construct has an average value of 3.91 and a Standard Deviation of 1.835, which suggests that the respondents have a **low level of agreement** and a **moderate degree of dispersion** around the average.

**Trust in Online Platforms (TOP)**

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| TOP1: I feel I can trust most online platforms where I shop for fast fashion items. | 3.99 | 1.647 | 0.907 |
| TOP2: I feel comfortable using online platforms to purchase fast fashion products. | 4.61 | 1.523 | 0.810 |
| TOP3: I believe most online platforms are truthful in their dealings with me. | 4.10 | 1.566 | 0.900 |
| TOP4: I believe most online platforms in the fast fashion industry act with my best interests in mind. | 3.52 | 1.773 | 0.892 |
| **Construct: Trust in Online Platforms** | 4.06 | 1.673 | |

*Source: Own elaboration based on SPSS and PLS outputs*

The Trust in Online Platforms (TOP) variable comprises four items as presented above. Among them, the item "TOP2: I feel comfortable using online platforms to purchase fast fashion products." has the highest average value of 4.61. On the other hand, the item "TOP4: I believe most online platforms in the fast fashion industry act with my best interests in mind." has the lowest agreement rate, with a mean of 3.52. It is noteworthy that this item exhibits the highest levels of variability in responses, as shown by the Standard Deviations of 1.773. In contrast, "TOP2: I feel comfortable using online platforms to purchase fast fashion products." demonstrates the lowest Standard Deviation value of 1.523, implying **moderate uniformity in the respondents' answers**. Therefore, the overall construct has an average value of 4.06 and a Standard Deviation of 1.673, which suggests that the respondents have a **moderate level of agreement** and a **moderate degree of dispersion** around the average.

### Ethics Position (Eth)

| Items | Mean | Std. Deviation | Loading |
| --- | --- | --- | --- |
| Eth1: A person should make certain that their actions never intentionally harm another even to a small degree. | 5.76 | 1.344 | 0.354 |
| Eth2: Risks to another should never be tolerated, irrespective of how small the risks might be. | 5.13 | 1.695 | 0.410 |
| Eth3: The existence of potential harm to others is always wrong, irrespective of the benefits to be gained. | 5.46 | 1.579 | 0.390 |
| Eth4: One should never psychologically or physically harm another. | 6.13 | 1.258 | 0.346 |
| Eth5: One should not perform an action which might in any way threaten the dignity and welfare of another individual. | 5.89 | 1.381 | 0.371 |
| Eth6: If an action could harm an innocent other, then it should not be done. | 6.05 | 1.276 | 0.414 |
| Eth7: Deciding whether or not to perform an act by balancing the positive consequences of the act against the negative consequences of the act is immoral. | 4.44 | 1.885 | 0.488 |
| Eth8: The dignity and welfare of people should be the most important concern in any society. | 5.87 | 1.323 | 0.384 |
| Eth9: It is never necessary to sacrifice the welfare of others. | 5.27 | 1.758 | 0.403 |
| Eth10: Moral actions are those which closely match ideals of the most "perfect" action. | 4.96 | 1.562 | 0.524 |
| Eth11: There are no ethical principles that are so important that they should be a part of any code of ethics. | 3.51 | 1.879 | 0.681 |
| Eth12: What is ethical varies from one situation and society to another. | 5.10 | 1.563 | 0.463 |
| Eth13: Moral standards should be seen as being individualistic; what one person considers to be moral may be judged to be immoral by another person. | 4.42 | 1.727 | 0.729 |
| Eth14: Different types of moralities cannot be compared as to "rightness." | 4.75 | 1.573 | 0.651 |

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| Eth15: What is ethical for everyone can never be resolved since what is moral or immoral is up to the individual. | 4.35 | 1.772 | 0.697 |
| Eth16: Moral standards are simply personal rules which indicate how a person should behave, and are not to be applied in making judgments of others. | 4.19 | 1.701 | 0.760 |
| Eth17: Ethical considerations in interpersonal relations are so complex that individuals should be allowed to formulate their own individual codes. | 4.32 | 1.583 | 0.736 |
| Eth18: Rigidly codifying an ethical position that prevents certain types of actions stands in the way of better human relations and adjustment. No rule concerning lying can be formulated; whether a lie is permissible or not permissible totally depends upon the situation. Whether a lie is judged to be moral or immoral depends upon the circumstances surrounding the action. | 4.41 | 1.644 | 0.581 |
| **Construct: Ethics Position** | 5 | 1.752 | |

*Source: Own elaboration based on SPSS and PLS outputs*

The variable Ethics Position (Eth) includes eighteen items as shown above. Among these items, "Eth4: One should never psychologically or physically harm another" has the highest average value of 6.13. On the other hand, "Eth11: There are no ethical principles that are so important that they should be a part of any code of ethics" has the lowest agreement rate, with a mean of 3.51. Notably, "Eth7: Deciding whether or not to perform an act by balancing the positive consequences of the act against the negative consequences of the act is immoral" exhibits the highest levels of variability in responses, as indicated by the Standard Deviations of 1.885. In contrast, "Eth4: One should never psychologically or physically harm another" demonstrates the lowest Standard Deviation value of 1.258, implying **greater uniformity in respondents' answers**. Therefore, the aggregate construct yields an average value of 5 and a Standard Deviation of 1.752, indicating that the respondents have a **moderate level of agreement** and a **moderate degree of dispersion** around the average.

## Overall Online Privacy (OPriv)

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| **Online Privacy Concerns (PCon)** | | | |
| PCon1: It usually bothers me when fast fashion websites ask for my personal information. | 5 | 1.677 | -0.391 |
| PCon2: When fast fashion websites request my personal information, I sometimes think twice before providing it. | 5.48 | 1.500 | -0.466 |
| PCon3: I am concerned that fast fashion websites are collecting too much personal information about me. | 5.29 | 1.519 | -0.452 |
| PCon4: I am concerned that when I give personal information to a fast fashion website for a specific reason, the website might use the information for other purposes. | 5.53 | 1.457 | -0.529 |
| PCon5: I am concerned that fast fashion websites might sell my personal information in their computer database to other companies. | 5.55 | 1.598 | -0.558 |
| PCon6: I am concerned that fast fashion websites might share my personal information with other companies without my authorization. | 5.53 | 1.576 | -0.590 |
| PCon7: I am concerned that fast fashion websites do not take enough steps to ensure the accuracy of my personal information in their files. | 5.09 | 1.643 | -0.491 |
| PCon8: I am concerned that fast fashion websites do not have adequate procedures to correct errors in my personal information. | 5.02 | 1.630 | -0.461 |
| PCon9: I am concerned that fast fashion websites do not devote enough time and effort to verify the accuracy of my personal information in their databases. | 4.76 | 1.678 | -0.440 |
| PCon10: I am concerned that databases containing my personal information in the fast fashion industry are not adequately protected from unauthorized access. | 5.47 | 1.512 | -0.572 |

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| **Online Privacy Concerns (PCon)** | | | |
| PCon11: I am concerned that fast fashion websites do not devote enough time and effort to prevent unauthorized access to my personal information. | 5.35 | 1.552 | -0.552 |
| PCon12: I am concerned that fast fashion websites do not take enough steps to ensure that unauthorized people cannot access my personal information in their computers. | 5.33 | 1.547 | -0.594 |
| PCon13: It usually bothers me when I lack control over the personal information I provide to fast fashion websites. | 5.14 | 1.642 | -0.448 |
| PCon14: It usually bothers me when I lack control or autonomy over decisions about how my personal information is collected, used, and shared by fast fashion websites. | 5.39 | 1.570 | -0.413 |
| PCon15: I am concerned when control is lost or unwillingly reduced as a result of a marketing transaction with fast fashion websites. | 5.39 | 1.456 | -0.409 |
| PCon16: It usually bothers me when the online privacy policy of fast fashion websites does not have a clear and conspicuous disclosure. | 5.32 | 1.560 | -0.309 |
| PCon17: It usually bothers me when I am not aware or knowledgeable about how my personal information will be used by fast fashion websites. | 5.48 | 1.524 | -0.377 |
| PCon18: It usually bothers me when fast fashion websites seeking my information online do not disclose the way the data are collected, processed, and used. | 5.54 | 1.448 | -0.402 |
| **Online Privacy Policies (PPol)** | | | |
| PPol1: Fast fashion websites disclose their information practices before collecting personal information from consumers. | 3.71 | 1.655 | 0.762 |
| PPol2: Consumers are given options regarding whether personal information | 3.91 | 1.694 | 0.806 |

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| collected from them by fast fashion websites may be used for purposes beyond those for which the information was provided. | | | |
| **Online Privacy Policies (PPol)** | | | |
| PPol3: Consumers are given options regarding how personal information collected from them by fast fashion websites may be used for purposes beyond those for which the information was provided. | 3.88 | 1.773 | 0.799 |
| PPol4: Consumers are able to view the accuracy and completeness of data collected about them by fast fashion websites. | 3.45 | 1.864 | 0.810 |
| PPol5: Consumers are able to contest the accuracy and completeness of data collected about them by fast fashion websites. | 3.37 | 1.830 | 0.813 |
| PPol6: Fast fashion websites take reasonable steps to ensure that information collected from consumers is accurate. | 3.78 | 1.827 | 0.806 |
| PPol7: Fast fashion websites take reasonable steps to ensure that information collected from consumers is secure from unauthorized use. | 3.61 | 1.784 | 0.820 |
| **Construct: Overall Online Privacy (OPriv)** | 4.85 | 1.794 | |

*Source: Own elaboration based on SPSS and PLS outputs*

The variable Overall Online Privacy (OPriv) is made up of twenty-five items and is divided into two dimensions: Online Privacy Concerns (PCon) with eighteen items and Online Privacy Policies (PPol) with seven, as displayed above. The items "PCon5: I am concerned that fast fashion websites might sell my personal information in their computer database to other companies" and "PPol2: Consumers are given options regarding whether personal information collected from them by fast fashion websites may be used for purposes beyond those for which the information was provided" received the highest average values of 5.55 and 3.91, respectively. On the other hand, "PCon9: I am concerned that fast fashion websites do not devote enough time and effort to verify the accuracy of my personal information in their databases" and "PPol5: Consumers are able to contest the accuracy and completeness of data collected about them by fast fashion websites" received the lowest agreement rates, with means of 4.76 and 3.37, respectively. Notably, "PCon9: I am concerned that fast fashion websites do not devote enough time and effort to verify the accuracy of my personal information in their databases" and "PPol4: Consumers are able to view the accuracy and completeness of data collected about them by fast fashion websites" exhibit the highest levels of variability in responses, with Standard Deviations of 1.678 and 1.864, respectively. Conversely, "PCon18: It usually bothers me when fast fashion websites seeking my information online do not disclose the way the data are collected, processed, and used" and "PPol1: Fast fashion websites disclose their information practices before collecting personal information from consumers" demonstrate the lowest Standard Deviation values, with 1.448 and 1.655, respectively, indicating **greater uniformity in respondents' answers**. Therefore, the combined construct has an average value of 4.85 and a Standard Deviation of 1.794, indicating that respondents have a **moderate level of agreement** and a **moderate degree of dispersion** around the average.

**Consumer Engagement (Eng)**

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| Eng1: I am passionate about the fast fashion industry. | 3.35 | 1.792 | 0.915 |
| Eng2: I am enthusiastic about trends in the fast fashion industry. | 3.61 | 1.971 | 0.886 |
| Eng3: Anything related to fast fashion grabs my attention. | 3.52 | 1.896 | 0.896 |
| Eng4: I am immersed in my interaction with trends in the fast fashion industry. | 3.37 | 1.889 | 0.921 |
| Eng5: In general, I thoroughly enjoy exchanging ideas with other fast fashion enthusiasts. | 3.25 | 1.957 | 0.916 |
| Eng6: When interacting with fast fashion trends, it is difficult to detach myself. | 2.87 | 1.765 | 0.870 |
| Eng7: When someone praises the fast fashion industry, it feels like a personal compliment. | 2.65 | 1.920 | 0.873 |
| Eng8: I am proud of the success of the fast fashion industry. | 3 | 2.024 | 0.892 |
| **Construct: Consumer Engagement** | 3.20 | 1.925 | |

*Source: Own elaboration based on SPSS and PLS outputs*

The variable Consumer Engagement (Eng) is constituted by eight items as listed above. Among these items, "Eng2: I am enthusiastic about trends in the fast fashion industry" has the highest average value of 3.61. In contrast, "Eng7: When someone praises the fast fashion industry, it feels like a personal compliment" has the lowest agreement rate, with a mean of 2.65. Notably, "Eng8: I am proud of the success of the fast fashion industry" shows the highest levels of variability in responses, with a standard deviation of 2.024. Conversely, "Eng6: When interacting with fast fashion trends, it is difficult to detach myself" has the lowest standard deviation value (1.765), implying **moderate uniformity in respondents' answers**. Overall, the aggregate construct has an average value of 3.20 and a standard deviation of 1.925, indicating that the respondents have a **low level of agreement** and a **high degree of dispersion** around the average.

### Overall Well-being (OW)

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| **Psychological Well-being (PW)** | | | |
| PW1: My fashion choices contribute to a sense of stability and satisfaction in my life. | 4.69 | 1.510 | 0.481 |
| PW2: I feel empowered to voice my concerns or preferences in my fashion choices, even within my social circles or family. | 4.83 | 1.547 | 0.499 |
| PW3: I feel in charge of my fashion choices, following my preferences rather than external influences (e.g., trends). | 5.58 | 1.256 | 0.112 |
| PW4: I feel I have a significant role in determining my fashion choices and what suits me within my social/family context. | 5.69 | 1.230 | 0.123 |
| PW5: I value the freedom to make my own fashion decisions based on personal preferences and individual style. | 6.01 | 1.057 | 0.104 |
| **Consumer Well-being (CW)** | | | |
| CW1: The quality of AI-driven recommendations significantly influences my satisfaction with fast fashion purchases. | 3.66 | 1.850 | 0.859 |
| CW2: AI-influenced pricing alignment with my fast | 3.66 | 1.831 | 0.846 |

| Items | Mean | Std. Deviation | Loading |
|---|---|---|---|
| fashion preferences and ethical considerations is crucial for my overall well-being in my fashion choices. | | | |
| **Consumer Well-being (CW)** | | | |
| CW3: AI customization plays a key role in impacting my choices and contributing to my well-being regarding sustainability preferences in fast fashion. | 3.50 | 1.884 | 0.905 |
| CW4: AI-driven customer service experiences have a substantial effect on my satisfaction with fast fashion, positively contributing to my overall well-being. | 3.62 | 1.776 | 0.897 |
| CW5: My satisfaction with AI-influenced fashion items is closely tied to considerations of sustainability and ethical dimensions, contributing to my overall sense of well-being. | 3.74 | 1.853 | 0.835 |
| CW6: AI-driven personalization significantly impacts my satisfaction with fast fashion, contributing to my overall sense of well-being. | 3.54 | 1.827 | 0.925 |
| CW7: Sustainability considerations have a notable impact on my satisfaction when disposing of AI-recommended items, contributing to my overall well-being. | 3.94 | 1.730 | 0.787 |
| CW8: AI integration significantly influences store ambiance during my fast fashion shopping, contributing to my overall well-being. | 3.51 | 1.793 | 0.873 |
| CW9: AI's influence on the availability of desired fast fashion items significantly affects my choices, contributing to my overall well-being. | 3.67 | 1.909 | 0.861 |
| CW10: My satisfaction with AI's impact on adopting more sustainable and ethical fashion styles is crucial for my overall well-being. | 3.78 | 1.891 | 0.815 |
| **Construct: Overall Well-being** | 4.23 | 1.887 | |

*Source: Own elaboration based on SPSS and PLS outputs*

The Overall Well-being (OW) variable entails fifteen items, which are further divided into two dimensions: Psychological Well-being (PW) with five items, and Consumer Well-being (CW) with ten items, as outlined above. The items "PW5: I value the freedom to make my own fashion decisions based on personal preferences and individual style." and "CW7: Sustainability considerations have a notable impact on my satisfaction when disposing of AI-recommended items, contributing to my overall well-being." received the highest average values of 6.01 and 3.94, respectively. Conversely, "PW1: My fashion choices contribute to a sense of stability and satisfaction in my life." and "CW3: AI customization plays a key role in impacting my choices and contributing to my well-being regarding sustainability preferences in fast fashion." received the lowest agreement rate, with means of 4.69 and 3.50, respectively. The items "PW2: I feel empowered to voice my concerns or preferences in my fashion choices, even within my social circles or family." and "CW9: AI's influence on the availability of desired fast fashion items significantly affects my choices, contributing to my overall well-being." showed the highest levels of variability in responses, with Standard Deviations of 1.547 and 1.909, respectively. In contrast, "PW5: I value the freedom to make my own fashion decisions based on personal preferences and individual style." and "CW7: Sustainability considerations have a notable impact on my satisfaction when disposing of AI-recommended items, contributing to my overall well-being." exhibited the lowest Standard Deviation values, with 1.057 and 1.730, respectively, indicating **greater uniformity in respondents' answers**. The average value of the aggregate construct was 4.23, with a Standard Deviation of 1.887, which suggests that respondents had a **moderate level of agreement** and a **moderate degree of dispersion** around the average.

**Blue Color Markers (BL)**

| Items | Mean | Std. Deviation |
|---|---|---|
| BL1: I like the blue color. | 5.54 | 1.331 |
| BL2: Blue makes me feel relaxed. | 5.27 | 1.402 |
| BL3: I often choose blue clothing items. | 4.37 | 1.813 |
| BL4: I prefer wearing blue footwear over other colored footwear. | 2.72 | 1.733 |
| **Construct: Blue Color Markers** | 4.48 | 1.927 |

*Source: Own elaboration based on SPSS outputs*

Lastly, the variable Blue Color Markers (BL) comprehends four items listed in Appendix C. Among these, the item "BL1: I like the blue color" received the highest average value of 5.54. However, the item "BL4: I prefer wearing blue footwear over other colored footwear" had the lowest agreement rate, with an average of 2.72. Interestingly, the item "BL3: I often choose blue clothing items" received the highest variability in responses, as indicated by the Standard Deviations of 1.813. In contrast, "BL1: I like the blue color" had the lowest Standard Deviation value of 1.331, suggesting that **respondents' answers were more consistent**. Therefore, the aggregate construct has an average value of 4.48 and a Standard Deviation of 1.927, indicating that the respondents have a **moderate level of agreement** and a **moderate degree of dispersion** around the average.

## Appendix D. Other Results

### Factor Loadings of the Blue Color Markers (BL)

| Dimension | Item's Loading | | | |
|---|---|---|---|---|
| | BL1 | BL2 | BL3 | BL4 |
| BL Marker 1 | 0.231 | 0.432 | 0.763 | 0.904 |
| BL Marker 2 | 0.110 | 0.297 | 0.682 | 0.932 |
| BL Marker 3 | 0.114 | 0.311 | 0.659 | 0.945 |
| BL Marker 4 | 0.060 | 0.264 | 0.649 | 0.935 |
| BL Marker 5 | 0.036 | 0.260 | 0.669 | 0.916 |
| BL Marker 6 | 0.531 | 0.636 | 0.724 | 0.876 |
| BL Marker 7 | 0.117 | 0.319 | 0.662 | 0.944 |
| BL Marker 8 | -0.108 | 0.089 | 0.525 | 0.922 |
| BL Marker 9 | 0.069 | 0.258 | 0.668 | 0.927 |

*Source: Own elaboration based on PLS outputs*

### Construct Reliability and Convergent Validity: With Markers

| With Markers | | | | |
|---|---|---|---|---|
| | Cronbach's alpha | Composite reliability (rho_a) | Composite reliability (rho_c) | Average variance extracted (AVE) |
| BL Marker 1 | 0.603 | 0.691 | 0.827 | 0.707 |
| BL Marker 2 | 0.603 | 0.729 | 0.824 | 0.703 |
| BL Marker 3 | 0.603 | 0.827 | 0.818 | 0.696 |
| BL Marker 4 | 0.603 | 0.747 | 0.823 | 0.702 |
| BL Marker 5 | 0.603 | 0.696 | 0.827 | 0.706 |
| BL Marker 6 | 0.603 | 0.912 | 0.813 | 0.690 |
| BL Marker 7 | 0.603 | 0.811 | 0.819 | 0.697 |
| BL Marker 8 | 0.603 | 0.711 | 0.826 | 0.705 |
| BL Marker 9 | 0.948 | 0.949 | 0.959 | 0.795 |
| BC | 0.965 | 0.966 | 0.970 | 0.803 |
| Eng | 0.717 | 0.718 | 0.876 | 0.780 |
| EnvMind | 0.849 | 0.863 | 0.890 | 0.619 |
| Eth | 0.949 | 0.952 | 0.956 | 0.665 |
| ExpAI | 0.948 | 0.949 | 0.958 | 0.764 |
| OPriv | 0.970 | 0.970 | 0.973 | 0.704 |
| OV | 0.963 | 0.967 | 0.968 | 0.752 |
| OW | 0.902 | 0.926 | 0.931 | 0.771 |
| TOP | 0.603 | 0.691 | 0.827 | 0.707 |

*Source: Own elaboration based on PLS outputs | BC: Brand Credibility, Eng: Consumer Engagement, EnvMind: Environmental Mindfulness, Eth: Ethics Position, ExpAI: Experience with Artificial Intelligence, OPriv: Overall Online Privacy, OV: Overall Values, OW: Overall Well-being, TOP: Trust in Online Platforms.*

## Direct Effects: With Markers

| With Markers | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Paths** | **Beta** | **Std. Deviation** | **T Statistics** | **P Values** | **CI (2.5%)** | **CI (97.5%)** | **VIF** |
| BC ➔ ExpAI | -0.024 | 0.079 | 0.299 | 0.765 | -0.173 | 0.137 | 2.168 |
| Eng ➔ OW | 0.368 | 0.062 | 5.983 | 0.000 | 0.245 | 0.484 | 2.239 |
| EnvMind ➔ ExpAI | 0.064 | 0.047 | 1.348 | 0.178 | -0.028 | 0.154 | 1.118 |
| Eth ➔ Eng | 0.166 | 0.052 | 3.172 | 0.002 | 0.068 | 0.273 | 1.208 |
| ExpAI ➔ OW | 0.513 | 0.057 | 8.996 | 0.000 | 0.401 | 0.625 | 2.194 |
| ExpAI ➔ TOP | 0.540 | 0.055 | 9.816 | 0.000 | 0.429 | 0.642 | 1.132 |
| OPriv ➔ Eng | 0.268 | 0.067 | 4.028 | 0.000 | 0.138 | 0.397 | 1.778 |
| OV ➔ ExpAI | 0.731 | 0.073 | 9.994 | 0.000 | 0.582 | 0.868 | 2.329 |
| TOP ➔ Eng | 0.330 | 0.060 | 5.507 | 0.000 | 0.209 | 0.444 | 1.535 |
| Eth x TOP ➔ Eng | 0.094 | 0.036 | 2.648 | 0.008 | 0.028 | 0.169 | 1.150 |
| OPriv x TOP ➔ Eng | 0.094 | 0.043 | 2.201 | 0.028 | 0.008 | 0.173 | 1.173 |

*Source - Own elaboration based on PLS outputs | BC: Brand Credibility, Eng: Consumer Engagement, EnvMind: Environmental Mindfulness, Eth: Ethics Position, ExpAI: Experience with Artificial Intelligence, OPriv: Overall Online Privacy, OV: Overall Values, OW: Overall Well-being, TOP: Trust in Online Platforms.*

## Cross Loadings

| Items | BC | Eng | EnvMind | Eth | ExpAI | OPriv | OV | OW | TOP | Eth x TOP | OPriv x TOP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BC1 | **0.876** | 0.553 | 0.149 | 0.209 | 0.504 | 0.491 | 0.666 | 0.568 | 0.634 | 0.058 | 0.016 |
| BC2 | **0.902** | 0.570 | 0.159 | 0.258 | 0.497 | 0.542 | 0.692 | 0.619 | 0.713 | 0.082 | 0.009 |
| BC3 | **0.894** | 0.507 | 0.116 | 0.241 | 0.470 | 0.502 | 0.612 | 0.532 | 0.584 | 0.097 | 0.007 |
| BC4 | **0.872** | 0.512 | 0.120 | 0.273 | 0.490 | 0.467 | 0.595 | 0.545 | 0.581 | 0.095 | 0.041 |
| BC5 | **0.888** | 0.533 | 0.091 | 0.240 | 0.464 | 0.557 | 0.682 | 0.519 | 0.652 | 0.069 | -0.030 |

| Items | BC | Eng | EnvMind | Eth | ExpAI | OPriv | OV | OW | TOP | Eth x TOP | OPriv x TOP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BC6 | **0.916** | 0.533 | 0.113 | 0.180 | 0.490 | 0.517 | 0.672 | 0.548 | 0.677 | 0.097 | -0.038 |
| CW1 | 0.581 | 0.656 | 0.242 | 0.361 | 0.712 | 0.490 | 0.731 | **0.870** | 0.554 | 0.137 | 0.226 |
| CW10 | 0.505 | 0.559 | 0.302 | 0.220 | 0.589 | 0.478 | 0.637 | **0.818** | 0.490 | 0.156 | 0.202 |
| CW2 | 0.544 | 0.639 | 0.231 | 0.286 | 0.669 | 0.466 | 0.672 | **0.851** | 0.518 | 0.183 | 0.265 |
| CW3 | 0.582 | 0.722 | 0.275 | 0.394 | 0.768 | 0.547 | 0.774 | **0.912** | 0.561 | 0.164 | 0.198 |
| CW4 | 0.593 | 0.694 | 0.242 | 0.349 | 0.721 | 0.517 | 0.735 | **0.897** | 0.567 | 0.107 | 0.201 |
| CW5 | 0.460 | 0.618 | 0.318 | 0.278 | 0.635 | 0.455 | 0.622 | **0.847** | 0.486 | 0.190 | 0.211 |
| CW6 | 0.605 | 0.696 | 0.258 | 0.365 | 0.748 | 0.491 | 0.777 | **0.927** | 0.586 | 0.135 | 0.226 |
| CW7 | 0.379 | 0.526 | 0.362 | 0.261 | 0.551 | 0.427 | 0.579 | **0.794** | 0.422 | 0.210 | 0.189 |
| CW8 | 0.559 | 0.690 | 0.315 | 0.359 | 0.716 | 0.507 | 0.722 | **0.876** | 0.574 | 0.157 | 0.194 |
| CW9 | 0.560 | 0.696 | 0.264 | 0.368 | 0.711 | 0.502 | 0.733 | **0.872** | 0.567 | 0.146 | 0.234 |
| EC10 | 0.090 | 0.123 | **0.752** | 0.137 | 0.173 | 0.045 | 0.127 | 0.204 | 0.009 | 0.087 | 0.144 |
| EC14 | 0.128 | 0.224 | **0.845** | 0.203 | 0.252 | 0.173 | 0.176 | 0.234 | 0.095 | 0.085 | 0.230 |
| EC8 | 0.108 | 0.208 | **0.755** | 0.163 | 0.223 | 0.119 | 0.206 | 0.311 | 0.104 | 0.054 | 0.248 |
| Eng1 | 0.552 | **0.915** | 0.223 | 0.356 | 0.654 | 0.506 | 0.640 | 0.660 | 0.530 | 0.287 | 0.246 |
| Eng2 | 0.530 | **0.886** | 0.175 | 0.350 | 0.615 | 0.474 | 0.608 | 0.627 | 0.470 | 0.220 | 0.181 |
| Eng3 | 0.520 | **0.895** | 0.203 | 0.334 | 0.655 | 0.455 | 0.624 | 0.646 | 0.494 | 0.210 | 0.239 |
| Eng4 | 0.502 | **0.921** | 0.241 | 0.373 | 0.649 | 0.495 | 0.646 | 0.682 | 0.479 | 0.261 | 0.248 |
| Eng5 | 0.521 | **0.916** | 0.206 | 0.360 | 0.684 | 0.509 | 0.679 | 0.698 | 0.508 | 0.265 | 0.204 |
| Eng6 | 0.537 | **0.870** | 0.229 | 0.450 | 0.642 | 0.558 | 0.653 | 0.676 | 0.539 | 0.290 | 0.234 |
| Eng7 | 0.524 | **0.873** | 0.254 | 0.431 | 0.663 | 0.638 | 0.665 | 0.690 | 0.574 | 0.285 | 0.305 |
| Eng8 | 0.607 | **0.892** | 0.202 | 0.370 | 0.685 | 0.623 | 0.713 | 0.707 | 0.614 | 0.273 | 0.241 |
| Eth11 | 0.260 | 0.420 | 0.101 | **0.733** | 0.359 | 0.329 | 0.348 | 0.374 | 0.309 | 0.186 | 0.134 |

| Items | BC | Eng | EnvMind | Eth | ExpAI | OPriv | OV | OW | TOP | Eth x TOP | OPriv x TOP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Eth13 | 0.218 | 0.261 | 0.110 | **0.776** | 0.269 | 0.215 | 0.251 | 0.244 | 0.259 | 0.071 | 0.117 |
| Eth15 | 0.097 | 0.260 | 0.166 | **0.780** | 0.248 | 0.178 | 0.199 | 0.212 | 0.155 | 0.088 | 0.208 |
| Eth16 | 0.234 | 0.342 | 0.281 | **0.804** | 0.395 | 0.241 | 0.317 | 0.324 | 0.290 | 0.067 | 0.230 |
| Eth17 | 0.180 | 0.323 | 0.197 | **0.840** | 0.316 | 0.234 | 0.259 | 0.279 | 0.185 | 0.162 | 0.212 |
| ExpAI1 | 0.454 | 0.576 | 0.211 | 0.377 | **0.814** | 0.407 | 0.538 | 0.591 | 0.481 | 0.093 | 0.174 |
| ExpAI10 | 0.454 | 0.609 | 0.240 | 0.327 | **0.849** | 0.388 | 0.604 | 0.666 | 0.446 | 0.121 | 0.176 |
| ExpAI11 | 0.366 | 0.581 | 0.295 | 0.315 | **0.835** | 0.384 | 0.557 | 0.605 | 0.443 | 0.139 | 0.228 |
| ExpAI12 | 0.367 | 0.602 | 0.313 | 0.276 | **0.795** | 0.462 | 0.516 | 0.576 | 0.387 | 0.218 | 0.239 |
| ExpAI13 | 0.392 | 0.637 | 0.262 | 0.403 | **0.832** | 0.488 | 0.593 | 0.676 | 0.422 | 0.241 | 0.243 |
| ExpAI14 | 0.311 | 0.507 | 0.260 | 0.265 | **0.715** | 0.360 | 0.458 | 0.540 | 0.324 | 0.182 | 0.101 |
| ExpAI2 | 0.450 | 0.565 | 0.197 | 0.357 | **0.852** | 0.397 | 0.576 | 0.633 | 0.467 | 0.165 | 0.174 |
| ExpAI3 | 0.582 | 0.580 | 0.154 | 0.275 | **0.783** | 0.457 | 0.768 | 0.694 | 0.535 | 0.114 | 0.131 |
| ExpAI4 | 0.482 | 0.714 | 0.237 | 0.448 | **0.859** | 0.473 | 0.693 | 0.745 | 0.509 | 0.183 | 0.242 |
| ExpAI5 | 0.417 | 0.628 | 0.274 | 0.366 | **0.870** | 0.408 | 0.617 | 0.680 | 0.461 | 0.135 | 0.223 |
| ExpAI6 | 0.542 | 0.548 | 0.112 | 0.286 | **0.751** | 0.452 | 0.758 | 0.634 | 0.542 | 0.148 | 0.110 |
| PEV1 | 0.654 | 0.552 | 0.170 | 0.245 | 0.641 | 0.509 | **0.842** | 0.658 | 0.582 | 0.122 | 0.088 |
| PEV2 | 0.671 | 0.606 | 0.233 | 0.360 | 0.647 | 0.527 | **0.876** | 0.706 | 0.604 | 0.081 | 0.082 |
| PEV3 | 0.619 | 0.503 | 0.164 | 0.258 | 0.616 | 0.432 | **0.832** | 0.672 | 0.592 | 0.126 | 0.085 |
| PEV4 | 0.612 | 0.551 | 0.177 | 0.325 | 0.628 | 0.525 | **0.852** | 0.673 | 0.556 | 0.175 | 0.157 |
| PEV5 | 0.661 | 0.566 | 0.199 | 0.311 | 0.613 | 0.533 | **0.853** | 0.704 | 0.640 | 0.162 | 0.119 |
| PPol1 | 0.518 | 0.511 | 0.115 | 0.319 | 0.462 | **0.819** | 0.569 | 0.481 | 0.538 | 0.133 | 0.085 |
| PPol2 | 0.544 | 0.508 | 0.103 | 0.228 | 0.468 | **0.866** | 0.565 | 0.483 | 0.485 | 0.184 | 0.123 |
| PPol3 | 0.504 | 0.503 | 0.188 | 0.285 | 0.451 | **0.871** | 0.561 | 0.485 | 0.470 | 0.156 | 0.092 |

| Items | BC | Eng | EnvMind | Eth | ExpAI | OPriv | OV | OW | TOP | Eth x TOP | OPriv x TOP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| PPol4 | 0.485 | 0.562 | 0.145 | 0.307 | 0.516 | **0.899** | 0.601 | 0.539 | 0.500 | 0.238 | 0.177 |
| PPol5 | 0.436 | 0.523 | 0.134 | 0.274 | 0.419 | **0.904** | 0.552 | 0.464 | 0.457 | 0.232 | 0.186 |
| PPol6 | 0.489 | 0.513 | 0.136 | 0.270 | 0.455 | **0.869** | 0.562 | 0.499 | 0.523 | 0.200 | 0.104 |
| PPol7 | 0.541 | 0.537 | 0.110 | 0.250 | 0.433 | **0.886** | 0.589 | 0.497 | 0.522 | 0.203 | 0.129 |
| PQV1 | 0.594 | 0.613 | 0.187 | 0.323 | 0.646 | 0.519 | **0.865** | 0.694 | 0.588 | 0.114 | 0.159 |
| PQV2 | 0.629 | 0.647 | 0.156 | 0.322 | 0.639 | 0.578 | **0.875** | 0.680 | 0.607 | 0.147 | 0.145 |
| PQV3 | 0.628 | 0.634 | 0.168 | 0.329 | 0.642 | 0.567 | **0.865** | 0.677 | 0.594 | 0.106 | 0.141 |
| PQV4 | 0.506 | 0.585 | 0.156 | 0.323 | 0.647 | 0.517 | **0.787** | 0.626 | 0.564 | 0.130 | 0.132 |
| PQV5 | 0.633 | 0.657 | 0.135 | 0.312 | 0.669 | 0.605 | **0.860** | 0.701 | 0.634 | 0.149 | 0.119 |
| PQV6 | 0.672 | 0.677 | 0.200 | 0.323 | 0.631 | 0.648 | **0.864** | 0.684 | 0.624 | 0.154 | 0.149 |
| PSV1 | 0.572 | 0.671 | 0.211 | 0.314 | 0.624 | 0.594 | **0.799** | 0.699 | 0.564 | 0.186 | 0.285 |
| PSV2 | 0.613 | 0.643 | 0.174 | 0.211 | 0.620 | 0.602 | **0.828** | 0.685 | 0.594 | 0.222 | 0.216 |
| PSV3 | 0.565 | 0.679 | 0.220 | 0.314 | 0.656 | 0.558 | **0.814** | 0.689 | 0.577 | 0.200 | 0.201 |
| PSV4 | 0.592 | 0.615 | 0.215 | 0.271 | 0.585 | 0.512 | **0.766** | 0.633 | 0.536 | 0.198 | 0.194 |
| TOP1 | 0.684 | 0.538 | 0.074 | 0.290 | 0.494 | 0.527 | 0.654 | 0.574 | **0.907** | 0.102 | 0.082 |
| TOP2 | 0.565 | 0.376 | 0.039 | 0.175 | 0.431 | 0.314 | 0.534 | 0.450 | **0.812** | 0.082 | -0.010 |
| TOP3 | 0.625 | 0.461 | 0.055 | 0.259 | 0.451 | 0.467 | 0.578 | 0.509 | **0.900** | 0.155 | 0.046 |
| TOP4 | 0.641 | 0.643 | 0.142 | 0.347 | 0.584 | 0.634 | 0.680 | 0.606 | **0.890** | 0.190 | 0.144 |

*Source: Own elaboration based on PLS outputs. |* ***Note:*** *Bold values indicate the items corresponding to each construct, representing higher values. | BC: Brand Credibility, Eng: Consumer Engagement, EnvMind: Environmental Mindfulness, Eth: Ethics Position, ExpAI: Experience with Artificial Intelligence, OPriv: Overall Online Privacy, OV: Overall Values, OW: Overall Well-being, TOP: Trust in Online Platforms.*