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Consumer Perceptions of AI Ethics in E-Commerce: Exploring Hyper-Personalization, Inferred Data, and Algorithmic Bias in Culturally Diverse Contexts

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ABSTRACT:
This thesis explores how consumers from different cultural backgrounds perceive and respond to three AI-driven practices in e-commerce: hyper-personalization, inferred data use, and algorithmic bias. It focuses on how they engage with these systems in everyday digital interactions. The study adopts an interpretivist philosophy and an abductive approach, and we apply Cultural Dimensions Theory and Trust Theory as interpretive lenses. A qualitative research method was employed with semi-structured interviews. The interviews were conducted with ten participants from six cultural backgrounds and participants were selected through purposive sampling to ensure cultural diversity.

The findings suggest that consumers do not passively accept AI-driven practices but engage with them conditionally. Their responses are shaped by perceived usefulness, system opacity, structural dependence on digital platforms and their backgrounds. Hyper-personalization is accepted in some way when it enhances convenience but resisted when it crosses personal boundaries. Participants tend to verify AI-generated recommendations rather than accepting them at face value. Three forms of trust were identified: outcome-based, process-based, and institution-based. These show different ways consumers deal with uncertainty. This is especially clear in opaque algorithmic systems. Perceptions of fairness were also not consistent, as participants interpreted fairness in different ways.

The study also points to two patterns that extend current literature: the autonomy paradox, refers to a gap that participants said they make free choices but at the same time, they described being influenced by algorithms; the transparency paradox shows a similar tension that even more disclosure does not always reassure users. In some cases, it creates more discomfort when users become more aware of data practices behind the systems.

Most participants were gradually accustomed with data being collected in the background as they interpreted that this seemed normal in everyday use. However, their responses their responses shifted when data trade-offs were made explicit, often leading to resistance. This suggests that how data practices are presented matters, and it is not just about the practice itself as reactions to inferred data also stood out when participants moved from rational thinking to emotional discomfort.

Cultural background influenced how participants interpreted these practices but did not strictly determine behavior, instead acting as a lens through which experiences were understood.

These findings also provide practical implications for firms, highlighting the need to carefully calibrate personalization, design transparency in more effective ways, adapt strategies across cultural contexts, and address accountability in AI-driven systems.

KEYWORDS: AI ethics, e-commerce, hyper-personalization, inferred data, algorithmic bias, consumer trust, cultural context

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1 Introduction

This first chapter gives an overview of the thesis and an introduction to the research topic. It begins with the background of the study, explaining the relevance of artificial intelligence (AI) in e-commerce and identifying the ethical and cultural issues that motivate this research. Based on this background, the research purpose, questions, and objectives are presented, followed by the definitions of key terms used throughout the thesis. Finally, the chapter concludes with a brief outline of the overall thesis structure.

1.1 Background of the Study

Artificial Intelligence has emerged as a transformative element in the world's digital economy in general, and within e-commerce in particular. Machine-learning algorithms, predictive analytics, and recommendation engines have embedded themselves in digital marketing, logistics, and customer-interaction channels, allowing technology to influence the way businesses interact with consumers. The trend indicates the transformation of digital commerce where AI-driven practices are integrated in most activities, offering firms more opportunities to improve efficiency, optimize operations, and strengthen customer engagement (Dwivedi et al., 2021). From consumer perspectives, AI-powered systems make online shopping easier by reducing the effort required to find products (Bhagat et al., 2023) and offering personalized recommendations that streamline the purchasing decision process (Beyari & Garamoun, 2022).

With the increased integration of AI systems in daily digital life, concerns have arisen about the broader ethical and social consequences of these systems as modern AI systems have come to play a growing role in shaping the environments in which consumers make their decisions (Tiribelli, 2024). They can influence the digital environment to shape what consumers can see, emphasize prioritized options, and influence the structures of choices. These processes often occur without full visibility of consumers on how decisions are made and how data are utilized, which raises the concerns of transparency, autonomy, and accountability (Tene & Polonetsky, 2013; Tiribelli, 2024). Ethical issues related to predictive data practices and the possibility of uneven results of automated systems in various categories of users have been noted in previous studies (Tene & Polonetsky, 2013; Mehrabi et al., 2021). Such systems can also become a source of causing inequality in digital markets when they are applied on a large scale (Mehrabi et al., 2021). In addition, AI-driven systems can infer data about consumers based on patterns obtained during past interactions even when such information has not been explicitly given (Tene & Polonetsky, 2013). Rather than directly substituting the consumer's choice, AI-based systems are more likely to shape the decision spaces by favoring a few choices, minimizing the occurrence of others, and directing attention to the digital interface (Tiribelli, 2024).

Trust is thus a key factor that affects consumer relationships with AI-supported e-commerce systems. Prior research on online trust highlights the importance of perceived risk, privacy protection, and service provider's trustworthiness in influencing consumer confidence (McKnight et al., 2002 ; Kim et al., 2008). However, AI-driven systems can complicate these dynamics as they make it hard for consumers to understand how operations are made, what data are being used, and who is ultimately responsible for outcomes (Shin, 2020). When consumers are unable to evaluate how algorithmic practices are generated or to what extent they can maintain any meaningful control over the results, traditional trust mechanisms can be undermined (McKnight et al., 2002). In this context, predictive machine-learning systems, as Tiribelli (2024) argues, do not just affect individual decisions but start to form the contexts within which the decisions are made. Consequently, people might feel that they are making a personal choice while their actions are being influenced by algorithms. This dynamic highlights a tension between perceived agency and actual system influence, with important implications for how individuals experience autonomy and freedom of choice in algorithmic decision environments. Ethical concerns surrounding AI, as Tiribelli (2024) argues, go beyond what any single system produces since they also involve how these systems quietly reorganize the spaces in which people encounter and make sense of AI-mediated interactions in their daily lives.

Digital platforms operate across markets characterized by different cultural norms, expectations, and regulatory environments, meaning that consumer responses to AI-mediated practices do not arise in culturally neutral settings. Hofstede's (2001) cultural dimensions framework offers a useful lens for thinking about such variation, distinguishing societies along dimensions such as individualism-collectivism, power distance, and uncertainty avoidance, each of which shapes how people relate to autonomy, authority, and risk. Existing research demonstrates that cultural orientations influence multiple dimensions of how consumers engage with technology-driven practices. For instance, cultural values shape observable digital engagement behaviors such as information-seeking and content sharing (Thompson & Brouthers, 2021), as well as trust-related perceptions and acceptance of AI-mediated services (Chi et al., 2023). As a result, similar AI-driven practices may be experienced and evaluated differently across markets. However, there remains limited research examining how consumers themselves perceive and make sense of these practices within their everyday e-commerce interactions.

On the basis of this understanding, the thesis explores how consumers from different cultural backgrounds perceive and respond to three issues: hyper-personalization, inferred data, and algorithmic bias, in AI-driven e-commerce systems. Rather than focusing on technical system features, the thesis attends to how such practices are experienced and interpreted by consumers in their everyday digital interactions. The study highlights the importance of considering human trust and ethical awareness in discussions surrounding the development and use of AI.

Although there has been an increasing number of research on ethical AI and algorithmic decision-making in digital markets over time, much of the existing research has focused on system performance, acceptance, or governance frameworks. Comparatively less attention has been given to consumers about perceptions, interpretations, and emotional responses to AI-driven practices in their daily e-commerce interactions, particularly when these practices often operate invisible ways. Additionally, few studies have examined consumer perceptions of AI in relation to individuals from various cultures where trust, fairness, and transparency may be defined differently. This gap highlights the need for a qualitative, consumer-centered study that examines how consumers interpret AI-mediated interactions within diverse digital and cultural environments.

1.2 Purpose of the Study and Research Questions

The study aims to explore how consumers in various cultural groups perceive and make sense of the presence of artificial intelligence (AI) in the e-commerce context. As AI technologies are increasingly integrated into digital contexts, where the absence of physical constraints allows algorithms to mediate most consumer interactions, they increasingly influence how consumers experience, interpret, and evaluate their interactions with online systems. In such contexts, AI-driven systems may shape decision-making processes and affect perceptions of fairness, autonomy, and control. Examining these responses is therefore important in understanding how trust, perceived fairness, and autonomy emerge in tech-mediated contexts, particularly as algorithmic systems increasingly substitute or supplement human judgment in shaping consumer interactions and decision-making processes (Shin, 2020; Tiribelli, 2024).

This research focuses on the examination of three interconnected developments of AI in e-commerce, namely hyper-personalization, inferred data, and algorithmic bias. These practices illustrate the way in which algorithmic systems extend their use of the collected data, both tacitly and explicitly, to presume choices and preferences. Research suggests that these systems bring ethical concerns regarding accountability and transparency though they could offer convenience and efficiency practices. Transparency and explainability are particularly critical for building trust in AI systems, as opaque algorithms can lead to user suspicion and reduced acceptance (Shin, 2020). Understanding how users from different cultural backgrounds perceive and respond to these AI-driven practices is therefore critical for developing transparent and trustworthy e-commerce systems. Through examining how individuals from different cultural backgrounds interpret and respond to AI-driven practices in digital contexts, the thesis aims to contribute to academic and managerial understanding of ethical AI in e-commerce, providing insights for developing transparent, trustworthy, and culturally adaptable systems.

1.2.1 Main Research Question

The thesis aims to examine how individuals from different cultural contexts respond to the use of artificial intelligence (AI) in e-commerce by focusing on three key concerns: hyper-personalization (when AI can suggest extremely close options), inferred data (when AI generates consumer data drawn from implicit behavioral patterns without explicit user recognition), and algorithmic bias (when AI produces systematically inequitable results for particular consumer segments.)

The main research question is: How do consumers from different cultural backgrounds respond to AI-driven practices such as hyper-personalization, inferred data, and algorithmic bias in e-commerce?

The research question is centered around perceptions, interpretations, and responses to ethical concerns that occur when consumers of various cultural backgrounds interact with AI-driven practices in online shopping, with particular attention to issues of trust, fairness, and autonomy.

1.2.2 Sub-Questions

To address the main research question, the thesis focuses on these sub-questions:

1. How do consumers from different cultural backgrounds understand and experience hyper-personalization, inferred data use, and algorithmic bias in AI-driven e-commerce environments?
2. How do consumers from different cultures perceive trust, fairness, and transparency when interacting with AI-driven systems in e-commerce contexts and what factors shape these perceptions?

3. What ethical concerns do consumers from different cultural backgrounds express regarding hyper-personalization, inferred data use, and algorithmic bias, and how do these practices affect their sense of autonomy in online shopping?

1.3 Objectives of the Study

1.3.1 Research Objectives

The objective of this thesis is to explore how consumers from different cultural backgrounds perceive and respond to AI-driven practices such as hyper-personalization, inferred data use, and algorithmic bias in the context of e-commerce. The thesis also seeks to understand how consumers from different cultural backgrounds perceive and interpret ethical issues related to trust, fairness, and transparency in AI technologies, within the context of their personal experiences.

To achieve this aim, the thesis is guided by the following sub-objectives:

1. To explore how consumers from different cultural backgrounds describe and interpret AI-based personalization and algorithmic influence in e-commerce decision-making.
2. To examine how consumers form perceptions of trust, fairness, and transparency in interactions with AI-driven systems in e-commerce contexts.
3. To explore ethical concerns related to hyper-personalization, inferred data use, and algorithmic bias as expressed by consumers from different cultural backgrounds.
4. To develop exploratory insights into how cultural context and individual experiences may influence perceptions of AI-driven personalization and its implications for consumer autonomy and decision-making.

1.3.2 Significance of the Study

Academic significance

The thesis aims to add to the ongoing debates at the interface of AI ethics, consumer trust, and cross-cultural issues in international business. Although existing research has provided valuable perspectives to the acceptance of AI and digital consumer behavior, the ethical and cultural aspect of the AI-mediated interaction remains very situational with diverse meanings across cultures. Rather than trying to define or measure these dimensions, this thesis uses an exploratory qualitative method of analyzing how cultural and social background determine the perceptions of trust, fairness, and transparency with in the context of using AI-enabled e-commerce systems. Through the interpretations and lived experiences of the participants, the thesis offers exploratory ideas that can be used to enhance the past studies and generate a better understanding of ethical consumer behavior.

Managerial significance

The thesis offers a consumer-centered understanding of how ethical concerns influence trust and acceptance of AI in e-commerce drawing on qualitative perspectives from diverse cultural and social background. For multinational corporations, these findings are vital for navigating the nuances of AI-driven practices across diverse cultural landscapes. Insights from this research can also help identify consumer expectations related to transparency, fairness, and responsible data use to further assist international firms in adapting their communication strategies, aligning AI practices with local norms, and implementing responsible AI approaches which can help them build the long-term trust and build sustainable customer relations in foreign markets.

Social and ethical relevance

With the growing level of integration of AI technologies into our daily business settings, their impacts raise questions of autonomy and fairness, as well as concerns about human dignity particularly concerning our ability to make meaningful choices on our own. The speed of technological advancement may outpace our ability to set ethical boundaries, at times blurring the line between personalization and manipulation, or between convenience and control. Against this backdrop, there is a growing need for continuous ethical reflection as algorithmic systems increasingly shape consumer experiences and decisions in ways that are not always fully transparent. Without continuous examination, certain forms of algorithmic influence risk becoming normalized and invisibly embedded in routine digital interactions, even when their implications for consumer choice are not fully obvious while it is necessary to ensure that AI systems are developed and governed in ways that are transparent, inclusive, and respectful of human values. Furthermore, these perspectives also help organizations proactively address those concerns in support of responsible AI use, as well as trust in culturally diverse market segments.

1.4 Definitions of Key Terms

Hyper-Personalization. Hyper-personalization is a form of advanced marketing approach that applies the use of AI and big data analytics to bring highly personalized experiences that are grounded on the individual preferences and behaviors as well as the contextual factors of a given user in real-time. Unlike old paradigm of segmentation strategy, which denotes customer groups, hyper-personalization allows one-to-one marketing by fine-grained contextual information at the individual customer level through machine learning paradigms based on supervised learning, unsupervised learning, and reinforcement learning to process consumer information. The implementation of hyper-personalization relies on technologies such as the natural language processing to process sentiment, recommender system to predict preferences, and generative AI to create dynamically-generated content, which deliver the exact content to a unique consumer at the right place and time in the form of text, image, and video (Patil et al., 2025).

Inferred Data. Inferred data is a specific type of personal data that is generated through analytical and deductive processes rather than being directly or indirectly obtained from data subjects themselves. According to Custers and Vrabec (2024), inferred data is any new data that was inferred through AI systems and algorithmic processing through and it is opposed to data that simply implies transferring already existing information. Such data is generated by advanced data analytics, in which algorithms are used to process gathered personal information to come up with new insights, predictions, and characteristics about individuals that they may not have explicitly provided or even be aware of themselves. The regulatory treatment of inferred data remains contested within European data protection frameworks, as it occupies an ambiguous position between observed facts and algorithmic predictions, raising particular concerns when inferences relate to health conditions, psychological states, or other sensitive personal characteristics (Custers & Vrabec, 2024).

Algorithmic Bias. Algorithmic bias is a systematic deviations the output of algorithms relative to some relevant normative standard; when the normative standard involves fairness or equality, such deviations can cause unequal treatment or disadvantageous treatment of some certain groups (Fazelpour & Danks, 2021). Algorithmic bias can occur in various phases of the algorithmic lifecycle, such as data collection, model design, and deployment, and may be due to data imbalance, modeling assumptions, optimization criteria, and a misalignment between system goals and societal norms (Fazelpour & Danks, 2021; Kordzadeh & Ghasemaghaei, 2022).

1.5 Structure of the Thesis

The thesis was divided into five main chapters. The first one is Chapter 1, the Introduction of the thesis background and motivation, discussing the growing integration of AI technologies in digital commerce and the ethical concerns surrounding hyper-personalization, inferred data use, and algorithmic bias. It also defines the main research question and sub-research questions, research objectives and the definition of key terms that are relevant to the study.

Chapter 2 provides a review of scholarly literature. It starts with the discussion of the development of AI-driven systems in e-commerce, such as how personalization evolved into hyper-personalization and the increasing role of AI in structuring consumer decision environments. The chapter then addresses privacy-personalization trade-off, inferred data utilisation, and the concern about algorithmic fairness and bias. The chapter presents the major theoretical insights and conceptual reference, conceptual framework to describe how the concerns of transparency, fairness, autonomy, and the use of data is perceived by the consumer.

Chapter 3 explains the methodology of the thesis. It outlines the research philosophy, strategy, and the data collection methods, the sampling process, participant selection across different cultural contexts, the procedures for data analysis and the considerations related to research credibility, dependability, and ethical compliance.

Chapter 4 presents and analyzes the empirical findings derived from the interview data. The results are organized thematically around consumers' experiences and interpretations of hyper-personalization, inferred data use, and algorithmic bias, their evaluations of trust and fairness, and their perceptions of autonomy in AI-mediated e-commerce interactions, as well as insights into how participants from different backgrounds describe and evaluate these practices.

Chapter 5 summarizes the thesis with a discussion of the findings and references to the existing literature and the overall academic discussions of the subject of ethical AI and cross-cultural consumer behavior. It lays out the theoretical and managerial consequences of the research, considers the constraints of the research, and offers future research proposals in the field of AI-based digital commerce and cultural diversity.

2 Literature Review

2.1 AI Adoption and Personalization in E-Commerce

2.1.1 AI in Marketing and Online Consumer Decision making

AI has become one of the key components of modern marketing practice, as it allows firms to understand the consumer preferences with an increasing accuracy, predict the purchasing behavior, and support decision-making throughout the online shopping journey. The integration of AI into digital commerce presents a broader transformation to data-driven marketing strategies with machine learning, automated analytics and behavioral data being used to improve the relevance, efficiency and responsiveness of consumer interactions (Kumar et al., 2024). One of the key contributions of AI to the marketing field is its ability to reduce the search effort and simplify the information processing: AI-driven applications allow consumers explore large product lines by filtering out unnecessary content and presenting the options that align their preferences (Bhagat et al., 2023; Beyari & Garamoun, 2022). According to Shankar (2018), AI improves the efficiency of retailing through the automation of decision support functions and the enhancement of firm’s ability to anticipate consumer needs. In the context of e-retailing, Bhagat et al. (2023) suggest that AI reduces search effort, increases convenience, and helps consumers select suitable products among numerous alternatives. When AI systems are perceived as easy to use, they strengthen consumers' purchase intentions, with trust, product consciousness, and social norms serving as key factors in technology acceptance (Bhagat et al., 2023). In addition, AI-implementing marketing systems also enhance the effectiveness of consumer decision-making by providing timely and contextually relevant cues (Beyari & Garamoun, 2022). These systems draw on customer historical behavioral data like browsing history and prior interactions to give suggestions that closely match customer preferences, helping consumers focus on relevant choices then streamlining the path from consideration to purchase decision (Beyari & Garamoun, 2022).

Although the literature highlights the functional role of AI in supporting online decision-making, consumer experiences of AI-driven guidance particularly in terms of perceived intrusiveness, discomfort, and cultural variation are not always central to this stream of research. In general, AI contributes to the online consumer decision-making process by making information processing easier, supporting personalized choice environments, and increasing the perceived usefulness in e-commerce.

2.1.2 From Personalization to Hyper-Personalization

Personalization in marketing has traditionally been described as tailoring marketing content and product offerings to be more aligned with customer preferences for improving relevance and perceived value. Vesanen (2007) categorizes this as a range of approaches starting from segment marketing, which relies on limited demographic or purchase data, to advanced forms requiring higher interaction. While segment-based personalization improves relevance over mass marketing, it typically offers no customer interaction and limited learning opportunities. Personalization practices became more dynamic and data-driven with the advancement of digital technologies; firms start to more utilize customer behavioral data, such as browsing history and prior interactions, into recommendation processes. In this regard, the recommender systems became a significant instrument to assist consumers in decision-making in digital environments. Behera et al. (2020) shows that algorithm-based recommender systems can create more dynamic recommendations than traditional collaborative filtering methods as they can process behavioral data in real time. Similarly, Nguyen and Hsu (2022) show that consumers' perceived usefulness of personalized recommendations varies by contexts, with segment-level recommendations often rated as more useful than highly individualized ones. Together, these findings suggest that there is a transition from rule-based personalization to behavior-driven systems that continuously change to adapt depending on the interactions of the user. However, personalization does not always result into positive experiences for the customers. Notably, Teepapal (2025) argues that AI-driven personalization does not affect customer engagement directly; instead, its influence is mediated by other factors such as trust and perceived usefulness. This observation supports the idea that the effectiveness of personalization is based not just on the technical precision but also on the interpretation and experience of personalized content by the consumer.

Modern developments in artificial intelligence and predictive analytics have led to hyper-personalization, a more specific and context-sensitive form of personalization. Jain et al. (2021) position digital clienteling as a vehicle for hyper-personalization, drawing on unified customer data, real-time information capture, and big data analytics to deliver tailored experiences. Compared to traditional methods, hyper-personalization makes greater use of real-time data and behavioral insights. Koralla (2025) describes hyper-personalization as relying on the continuous integration of multiple data sources and real-time behavioral signals to dynamically adapt content to individual consumers. Consumer research also gives more insights on the responds of customers to hyper-personalized environment. Mehmood et al. (2025) demonstrate that consumers in fashion e-commerce are more likely to give a positive response to hyper-personalized experience when motivated by hedonic and utilitarian factors, and when they are given opportunities to co-create through customization that aligns with personal preferences. Their findings further indicate that such adaptive behavior strongly predicts re-patronage intentions, suggesting that consumers who engage positively with hyper-personalization are more likely to return to and recommend personalized retail environments. Overall, the transition from personalization to hyper-personalization shows a broader transformation in how digital marketing systems interact with consumers, when personalization becomes increasingly adaptive and data-intensive, it becomes more important in structuring consumer choice environments and shaping experiences in the modern digital commerce platform.

2.1.3 The Privacy-Personalization Trade-Off

One of the common themes found in the literature concerning digital consumer behavior is the privacy-personalization trade-off which explains why, on the one hand, consumers expect to receive personalized services; on the other, consumers are worried about the possible loss of privacy related to disclosure of data. The initial research on privacy has focused more on the fact that people understand privacy as the ability to have control over personal information, and concerns normally arise when such information may be misused, shared without user consent or when it is used in a way that user cannot predict (Culnan & Armstrong, 1999, pp. 105-106). This finding still influences modern study, especially because personalization technologies increasingly require extensive consumer data.

To explain how consumers navigate this trade-off, researchers have developed several theoretical frameworks. The privacy calculus is one of the explanatory frameworks used to explain the willingness of consumers to give up privacy in favour of benefits. Based on this construct, individuals weigh the perceived benefits (e.g., convenience, personalization, discounts) against the perceived costs (e.g., loss of privacy, misuse of data) before deciding whether to disclose personal information (Culnan & Armstrong, 1999, p. 106). Further empirical work has examined how specific factors, such as the type of information requested, the degree of consumer control over its subsequent use, and the potential consequences and benefits offered in exchange, which shape the outcome of this trade-off (Phelps et al., 2000, pp. 28-31). This is however not always rational in practice. Fernandes and Pereira (2021) reveal that habitual behavior also plays a significant role in the data-sharing choice, and consumers often share information automatically without actively reassessing potential risks. Consumer data disclosure can be influenced by both rational considerations and non-conscious processes. In the context of AI-mediated e-commerce where personalization is continuously embedded, this can reduce the attention to data privacy issues when data-sharing behaviors become more frequent.

However, there are still questions about if the privacy calculus can fully explain about consumers behavior in making data-disclosure decisions as in reality there are posibilities customers cannot calculate exactly costs and benefits each time before they make decision. Consumers also share their data in such situations where systems information is limited transparency, decisions are habitual, or when digital environments affect user careful consideration. This limitation is reflected in the well-known privacy paradox, which outlines the disconnect between how the consumers talk about privacy and their actual behaviour, Norberg et al. (2007) show that what consumers say about their privacy concerns does not reliably predict what they do in practice. As perceptions of risk shape disclosure intentions, they do not significantly predict actual disclosure behavior. From another perspective, Martin (2020) suggests that consumer behavior should not be treated as a reliable indicator of privacy preferences because the privacy paradox rests on a flawed assumption that disclosing information equates to relinquishing privacy expectations (Martin, 2020, pp. 66-67). These concerns become more pronounced in AI-based digital systems in which consumers might have limited knowledge about how algorithm systems gather, process, and infer additional data about their behavior. As personalization practices are based on complicated and opaque data practices, what consumers perceived about their privacy risk may differ from their privacy risks.

In addition, research also shows that consumers respond to the privacy-personalization trade-off in varied and sometimes unexpected ways. Karwatzki et al. (2017) show that personalization practices can enhance the perceived relevance and value while at the same time it also increases the privacy concerns because they require the disclosure of detailed and sometimes sensitive personal data. (Karwatzki et al., 2017). This suggests that consumers do not simply trade privacy for personalization benefits as they may experience increased value of personalization and increased privacy concerns at the same time. Importantly, the study shows that transparency features alone do not necessarily increase consumers' willingness to share their personal data. When more information about the data practices is provided, it does not increase the intentions of customers to disclosure their data (Karwatzki et al., 2017, pp. 389-390). The authors also suggests that consumer responds are vary according to one's privacy valuation: consumers with lower privacy valuation are more ready to provide information in highly personalized services while consumers with higher privacy valuation remain reluctant regardless of the level of personalization. Notably, Karwatzki et al. (2017) offer a potential explanation through what they describe as a duality of effects. While transparency features can signal fairness, they also make consumers more aware of how much data is being collected. As a result, transparency may heighten privacy concerns rather than reduce them. This challenges the common assumption that greater transparency necessarily encourages information disclosure.

2.1.4 AI-Driven Decision-Making in E-Commerce

The use of AI in the form of recommendation systems is becoming more common in how consumers navigate online marketplaces. These systems support consumer decision-making in an e-commerce setting by increasing convenience and improving access to product information (Beyari & Garamoun, 2022). In this sense, AI works as a data-filtering mechanism that can narrow large product selections and direct consumers toward options more suited to their needs and preferences. Beyond passively supporting decisions, these systems actively shape product visibility by drawing on behavioural data and cross-user patterns to fill consumer consideration sets (Beyari & Garamoun, 2022). As a result, consumers largely engage with algorithmically prioritised options, which limits the range of alternatives they consider (Beyari & Garamoun, 2022). Ultimately, AI does not merely affect consumer decision-making by providing information but fundamentally structures how information is filtered and presented.

Not only supporting in the short term in decision support, AI-driven recommendation systems can also influence consumer behavior over time. Research indicates that the more the consumers perceive that the recommendation systems are useful as they can enhance the outcome of the decision, the more they tend to adopt and and integrate it into their routine shopping behavior (Cabrera-Sanchez et al., 2020). As consumers repeatedly engage with personalized suggestions, AI systems may create habitual reliance on curated options, as reflected in behavioral signals such as increased clicking intentions. Yin et al. (2025) present evidence that AI-personalized suggestions are associated with higher clicking intentions, suggesting that algorithmic personalization influences not only the shopping experience but also consumer responses at a micro-behavioral level.

Consumers who trust AI interactions are more likely to select products or services provided by these systems. Teodorescu et al. (2023) find that trust in e-commerce AI is significantly associated with transparency, familiarity with other AI technologies, and the perceived usefulness of AI recommenders. Conversely, Omrani et al. (2022) suggest that concerns related to discrimination, accountability and the lack of a clear complaint mechanism are negatively associated with trust; when users perceive higher risks of biased outcomes or unclear responsibility in the AI-driven system, their trust tends to erode.

Studies further show that AI-based recommendations influence consumers' perceptions of the digital platform and also their relationships with digital platforms. Hassan et al. (2025) suggest that personalized recommendations are linked to higher satisfaction and loyalty when consumers perceive them as relevant and beneficial, though the effects are conditional on personalization quality. This shows that AI systems influence both decision outcomes and consumer engagement with digital platforms, as consumers are more likely to trust and rely on algorithmic guidance over time in case they find the suggestions useful. Although AI-driven recommendation systems can improve convenience and efficiency, it also raises concerns about transparency, consumer autonomy, and the extent to which algorithmic systems influence decision-making without users fully understanding of how such processes are operated.

2.2 Theoretical Perspectives

This research examines consumers' responses regarding ethical challenges related to AI-driven practices in digital business environments, particularly concerning trust, fairness, autonomy, and data use. Since technological characteristics alone cannot fully account for these perceptions as they are shaped by consumers' value orientations and their assessments of AI systems in decision-making and personalization contexts, this research adopts an interdisciplinary theoretical approach that combines cultural and behavioral perspectives to explain how consumers interpret, evaluate, and respond to AI-enabled practices in digital commerce. The theories that are presented in this section become interpretive lenses to support the analysis of the ethical concerns.

2.2.1 Cultural Dimensions Theory

The Cultural Dimensions Theory developed by Hofstede provides a widely used framework for explaining the ways in which cultural values shape individual attitudes and behaviors (Hofstede, 2001). In this theory, culture is conceptualized as a collective programming of the mind that distinguishes the members of one group or category of people from others (Hofstede, 2001). Among the cultural dimensions that Hofstede has proposed, individualism and collectivism are especially relevant in understanding how individuals balance personal and collective interests.

Personal autonomy, individual rights, and control of information are often emphasized in individualistic societies (Hofstede, 2001). In such contexts, consumers may place greater emphasis on privacy, transparency, and control over personal information. In contrast, collectivist societies focus on social cohesion, group interests, and interdependence. This orientation may lead to greater acceptance of data sharing when these practices are seen to support collective or social benefits. Research studies carried out empirically in digital fields provide support for the applicability of cultural dimensions in explaining attitudes toward privacy. In their study of Vietnamese university students, Nguyễn and Hà (2025) show that individual-level cultural orientations, specifically collectivism, long-term orientation, and uncertainty avoidance, are positively associated with privacy concern and indirectly influence privacy behavior through privacy concern, even within a single national context. They argue that cultural values at the individual level influence how people perceive and manage their online privacy, suggesting that privacy attitudes may vary among individuals within the same country rather than being uniform across a national population.

Other than privacy, cultural dimensions have also been found to influence the development of trust in e-commerce. Hallikainen and Laukkanen (2018) show that national culture helps explain variation in consumer trust in online vendors, particularly through its influence on disposition to trust. Their work reveals that collectivism and long-term orientation are significant predictors of disposition to trust, while other cultural dimensions such as uncertainty avoidance, power distance, and masculinity do not significantly influence disposition to trust directly, although uncertainty avoidance negatively affects context-specific perceptions of an online store's trustworthiness. These findings suggest that the formation of trust in e-commerce is shaped by broader cultural orientations and that the relationship between cultural dimensions and trust varies depending on the specific dimension examined.

Recent studies extend the application of cultural dimensions to interactions with AI systems. As Schwanz et al. (2025) find, personal cultural values such as collectivism, power distance, and long-term orientation are associated with differences in user performance in AI-supported decision tasks, with effects varying across task conditions. This indicates that cultural dimensions influence human technology interactions, including those involving AI-based decision-support tools. Cultural values also operate at the societal and institutional levels, shaping expectations around AI governance and public trust. Robinson (2020) shows that trust and transparency are consistently embedded cultural values in Nordic countries' national AI strategies, while openness is less prominently reflected. This highlights the impact of cultural orientations beyond individual perceptions, extending to collective expectations regarding responsible AI implementation, transparency, and accountability. The findings are relevant to international business, as they explain why AI applications aligned with cultural values in one country may face opposition or ethical concerns in another.

In this research, the individualism and collectivism dimension is used as an interpretive lens to explain cross-cultural differences in how consumers perceive privacy, trust, and ethical issues related to AI-driven personalization in digital commerce environments. It also provides a structured way to examine how cultural value orientations influence consumer expectations about data use practices, algorithmic transparency, and autonomy.

Differences in individualism and collectivism may shape how consumers perceive hyper-personalization, especially in terms of perceived autonomy and comfort with highly tailored recommendations. Cultural expectations also influence how the use of inferred data is interpreted, particularly with respect to privacy awareness and acceptable data boundaries. Furthermore, cultural expectations related to justice and equality may influence how algorithmic bias is perceived across contexts.

2.2.2 Trust Theory in AI-Mediated Contexts

Trust Theory provides a foundational lens for understanding how users judge and react to the AI systems, especially in situations that can be perceived as being uncertainty, lack of transparency and explainability (McKnight et al., 2002; Lukyanenko et al., 2022). Consumers tend to trust AI-driven systems, e.g. recommendation systems, automated decision-making tools, and personalized interfaces, in digital commerce settings without knowing how these systems are operated and what information is used. Trust therefore becomes a critical mechanism that enables continued interaction with AI even with lack of transparency or technical knowledge.

Building on earlier work on trust in online environments, McKnight et al. (2002), conceptualize trust as comprising perceptions of competence, integrity, and benevolence. This conceptualization has been applied broadly to the AI systems whereby users not only determine whether the technology is functioning properly, but also whether it acts fairly, transparently, and responsibly. Trust is no longer a purely interpersonal phenomenon but rather one that includes human-technology associations, as the AI system moves towards more autonomous or semi-autonomous actions (Ferrario et al., 2019).

The study on trust in AI reveals that the trust is highly influenced by the impressions of the users about the properties of algorithms. Shin (2020) shows that perceived fairness, accountability, transparency, and explainability are among the key factors to influence the trust of AI-driven personalization systems. Users might tend to view the system as trustworthy and helpful when they feel that algorithmic decisions are fair and comprehensible. These findings suggest that trust in AI depends not just on its performance outcomes, it is influenced as well by the way decisions are explained and justified to users. Moreover, trust in AI evolves with time. Cabiddu et al. (2022) distinguishes between initial trust and trust over time, noting that early trust judgments are usually made under the circumstances of low experience and high uncertainty. Initial trust is influenced by users' personal tendencies, how transparent the system appears, and whether the algorithm seems human-like in terms of qualities such as competence and benevolence. Trust may become stronger or weaker as the users become familiar with the system and assess its consistency, reliability, and alignment to their expectations. Such dynamic quality of trust is especially relevant in AI-enabled digital markets, where machine learning systems adapt and adjust their operation over time, potentially shifting the perception of the users.

Trust in AI can be formed differently depending on how AI systems are implemented in digital market interactions. In some contexts, users can view AI based on system-oriented attributes such as reliability, consistency, and performance, particularly when AI is used as a functional tool to support decision-making. In other contexts, trust is formed by perceptions of whether the system acts in users' interests, especially when AI interfaces appear personalized or interactive. Lukyanenko et al. (2022) state that trust in AI can be the result of the complexity of all these dimensions, including emotional and cognitive assessment of a system. This is highly relevant to the research because similar AI applications may be interpreted differently across markets, influencing user acceptance and trust formation. Trust can be undermined when AI-based suggestions start to seem discriminative or contrary to the interests of the user, decreasing the likelihood of acceptance and interaction. Grimmelikhuijsen (2022) demonstrates that even when the technology is advanced, a lack of algorithmic transparency can significantly undermine the perceived trust of automated decision-making. This indicates that trust in AI hinges largely on the clarity and accessibility of its decision explanations, not solely on technical performance. As standardized AI systems are implemented in various cultural contexts by global businesses, there can be a lack of alignment of system design and the local expectations of trust. Trust Theory therefore supports comparative analysis of how AI systems are evaluated across markets and promotes the necessity of adaptive systems of trust-building in international digital markets.

There is also recent research that has pointed to the possibility of ethical risks posed by trust in AI-mediated interactions. Focusing on the "dark side" of AI anthropomorphism, Hasan et al. (2025) proposes how human-like design features in service provisions can foster misplaced trustworthiness. Their framework offers a critical distinction: misplaced cognitive trustworthiness, where users overestimate an AI's capabilities, and misplaced affective trustworthiness, where users form unwarranted emotional bonds with AI systems. This misplaced trust is amplified by both machine-related deceptive techniques and consumer-related vulnerabilities, leading to adverse outcomes such as privacy violations, diminished autonomy, and distorted attribution of moral responsibility. This perspective is critical because it brings new angle to the concept of trust not merely as a facilitator of AI adoption, but it is as a possible source of ethical concerns in the context of e-commerce where anthropomorphic and hyper-personalized interfaces are increasingly prevalent.

This thesis uses Trust Theory to examine how consumers form and adjust the trust to AI-practices in e-commerce systems toward the perceptions of fairness, transparency, and accountability. As trust is not a constant outcome, the theory offers a frame explaining the aspect of trust as a dynamic assessment which is influenced by system features, user experience and contextual anticipations. This view is fundamental in investigating the impact of AI practices on consumer adoption and the sense of ethics in culturally diverse digital markets. Although hyper-personalized practices can build trust when consumers perceive them as useful and relevant, but it also can undermine consumer trust when they are perceived to imply overuse of data, lack of transparency or lack of autonomy. Also, trust can be undermined when there are unacknowledged data that the users do not know how they were operated and used. Additionally, the perceived bias of algorithms has a direct impact on the trust in AI systems, since biased and inconsistent results can destroy the perceptions of competence and integrity of the systems.

2.2.3 Responsible AI Principles as a conceptual reference

In addition, we use Responsible AI principles in our research as a conceptual reference to support the examine on ethical issues that are related to AI-driven practices in e-commerce. The framework developed by organizations such as the OECD highlight keys themes including fairness, transparency, accountability, privacy protection, and human oversight. These themes provide a common vocabulary source to discuss the ethical challenges that are regularly emerging in connection to the use of AI in digital business systems. This inquiry will rely on the Responsible AI concepts to understand how users view specific AI-driven practices such as hyper-personalization, use of inferred data, and algorithmic bias e-commerce systems. The principles provide a template to explain how the participants describe concerns that are related to fairness, privacy, transparency, and perceived autonomy when considering their interplay with the AI-driven personalization and recommendation systems. Responsible AI principles can therefore be used to define and explain how the ethical issues are expressed by the participants. This approach allows us to analyze similarities and differences of individuals from different cultural backgrounds perceive AI-driven practices and keep the focus on the personal experiences and interpretations of the participants. While applying the principles of Responsible AI, we will be able to discuss ethical perceptions in a structured manner that remains closely aligned with the exploratory and perception-based nature of the study.

2.2.4 Theoretical Synthesis

Taken together, Cultural Dimensions Theory and Trust Theory offer complementary perspectives for understanding how consumers interpret and respond to AI-driven practices in e-commerce. Cultural Dimensions Theory supports us to understand why consumers from different cultural backgrounds respond to AI and shape their expectations toward privacy, autonomy, and acceptable levels of personalization, thus explaining why consumer from different background can perceive similar AI practices differently. Trust Theory in its turn explains the impact of evaluations of fairness, transparency, and accountability on the expectation of consumers to place their trust in AI-driven recommendations and automated decisions, especially in situations where there is a lack of transparency in the algorithmic operations.

Responsible AI principles are incorporated alongside these theories as a conceptual reference, It is used for supporting the interpretation of ethical concerns that consumers perceived related to hyper-personalization, the use of inferred or “ghost” data, and algorithmic bias. In this research, we use these principles to provide common terms for interpreting how participants articulate ethical concerns arising from their interactions with AI-powered e-commerce systems. This approach allows ethical issues to be examined in a structured manner without interrupting participants’ own experiences and interpretations.

Together, these theoretical perspectives form a coherent theoretical background to help us analyze consumer perceptions of AI-driven practices in e-commerce. They bring a combined lens for understanding about ethical concerns emerge at the intersection of cultural context, trust formation, and AI-enabled personalization, particularly in relation to data use and algorithmic decision-making. We apply these theoretical perspectives in the research to guide the design of the qualitative research and the interpretation of interview data as Cultural Dimensions Theory helps us to design interview questions and analysis by showing how cultural differences may influence consumer expectations regarding privacy, autonomy, and acceptable levels of personalization while Trust Theory helps us to the interpretation of participants’ responses by explaining how concerns related to fairness, transparency, and data use that can affect trust in AI-driven e-commerce practices.

2.3 Ethical Concerns in AI-Driven E-Commerce

With the implement of AI in e-commerce platforms, ethical concerns have emerged as a central factor that influences consumer trust, platform legitimacy, and the sustainability of digital business models. These ethical concerns do not arise from one particular factor but they can reflect the interaction between AI practices, algorithmic decision-making processes, and the ways how AI-driven systems influence consumer autonomy in digital settings. Prior studies have suggested that how consumers perceive AI-driven services is related to their perceptions of data use, fairness, transparency, and control, particularly when such systems operate in different cultural and regulations.

Building on the theoretical perspectives presented in Section 2.2, in this section we review the key ethical issues related to AI-driven e-commerce through the lens of consumer-oriented. Specifically, it examines how AI-enabled data practices affect privacy, informed consent and the use of inferred data (Section 2.3.1), how algorithmic bias and fairness concerns influence trust in digital markets (Section 2.3.2), how AI-driven recommendation systems shape consumer autonomy and decision-making (Section 2.3.3), and how cultural and market contexts condition ethical perceptions of AI practices across different societies (Section 2.3.4). Together, these strands of literature provide an integrated foundation for understanding the ethical aspects that inform consumers' responses to AI-powered e-commerce platforms and guide the analysis in the following chapter.

2.3.1 Data Privacy, User Consent, and AI-Driven Inferred Data Use in Digital Commerce

As digital commerce increasingly depends on data-driven technologies, privacy and consent have become central ethical concerns shaping consumer trust and platform legitimacy. Research shows that tensions arise because firms' growing capabilities to collect and analyse consumer data frequently that exceeds the awareness of users of how their personal data is captured, processed, or reused. Quach et al. (2022) describe these as structural tensions inherent in digital environments. They note that many consumers do not understand what firms do with the data they collect, and a significant number feel unable to protect their data due to a lack of knowledge and the complexity of the processes involved. This is closely tied to the privacy paradox, the persistent observation that users voice concerns about privacy yet continue to disclose personal information. Herriger et al. (2025) attribute this to limited mental processing ability, cognitive biases, and knowledge deficiency. Drawing on a systematic review of privacy concerns in emerging technologies, they further suggest that privacy expectations are very context-specific; users are often unaware of what data are being collected or how they are being interpreted. In AI-driven settings, this discrepancy grows. The cognitive load of considering privacy notices is high, and online consent mechanisms may not help people make informed decisions when they are overloaded with consent requests, particularly when privacy policies remain unclear or inaccessible (Herriger et al., 2025). Taken together, these findings suggest that privacy issues in digital commerce go beyond the technical threat of data misuse but they also stem from the gap between users' expectations and how their data are actually collected and used.

The issue of privacy is heightened when digital systems do not just take into consideration data that are explicitly provided, but also other attributes that are inferred. The studies of large language models show that systems have the ability to produce sensitive or personal inferences based on apparently harmless interactions with a user and stored through the processes of retention in internal memory. According to Zhang et al. (2024), users often do not know about the existence of such inference mechanisms and are not aware that prior inputs can be reconstructed into fresh and sensitive inferences. They find that significant transparency gaps: users are unaware of the information being maintained, they cannot predict how inferences are made, and they do not have meaningful power over information that they never intentionally provided. These results highlight the extent to which the boundaries of privacy risk can be extended through the development of new inference capabilities, and raising concerns about user expectations of control over their interactions with AI-mediated settings. The concerns of inferred data become more intensified by the limits of current data protection laws. Custers and Vrabec (2024) explain that inferred data is created by data controllers rather than directly given by individuals, which makes its legal status under the GDPR uncertain. Even when this type of data is treated as personal data, it is not always clear how rights such as access, rectification, and data portability apply, and in some cases these rights only apply in a limited way. As a result, users may not have sufficient legal tools to properly understand, control, or challenge personal data that they did not knowingly share.

Data privacy issues at the governance level also intersect with international differences in regulatory settings and, as a result, influence how digital firms operate across markets. According to Yan (2024), the differences in data protection regimes have a strong influence on cross-border e-commerce, with stricter privacy frameworks such as the GDPR increasing compliance obligations and constraining cross-border data flows. These regulatory pressures affect firms' ability to engage in international digital trade, requiring adaptations in consent processes and data handling practices, illustrating how privacy regulation functions not only as a consumer protection measure but also as a structural economic barrier in cross-border e-commerce. Another study from Li et al. (2024) shows that privacy regulation can reshape global digital competition. Through examining how the European Union General Data Protection Regulation (GDPR) influenced the international mobile app market, the authors determine that the increased privacy in the form of data rights, access, deletion, and consent regulations, impacted the supply-side behavior and the demand. It is important to note that GDPR minimized privacy-related uncertainty among consumers in the EU, hence enhancing confidence in foreign apps as opposed to decreasing cross-border digital interaction. Their results show that effective and open governance structures can reduce the privacy issue and, counterintuitively, promote global online commerce by eliminating the information asymmetry and creating user trust in the data-handling conduct.

Taken together, these studies show that privacy, consent, and data governance in online trade are influenced by a three-fold combination of non-transparency of data practices, the ability of AI systems to make inferences, and the disjointed regulatory environment of online interactions. These dynamics enhance the concept that privacy is not a legal or technical problem but a foundational component of digital business strategy. Firms need to reconcile their data behaviors with the anticipations of the users, the transparency of both the explicit and inferred data, and the various regulatory frameworks which impact the processes of providing digital services across jurisdictions. For firms that operate across both domestic and global digital markets increasingly depend on their capacity to navigate these complexities, as doing so is essential for preserving user trust, enabling responsible AI practices, and remaining competitive in tightly connected digital economies.

2.3.2 Algorithmic Fairness and Bias in Digital Markets

Algorithmic fairness becomes crucial when digital markets are becoming more dependent on AI-driven practices, since in these environments, the bias is seen as perceived unfairness, which influences users evaluate the validity and reliability of the AI outputs. Systematic review of empirical studies shows that users judge algorithmic decisions on several aspects, such as the fairness of outcomes, the perceived neutrality of decision rules, and the transparency of information provided (Starke et al., 2022). When algorithms generate outputs that seem not equal, obscure, or dependent on non-relevant variables, users are more likely to view these outputs as biased outputs or discriminatory. Such bias can develop in a variety of forms, as Tsamados et al. (2022) note, technical and design choices built into algorithmic systems including biased training data and flawed model design, can reinforce existing structural inequalities, especially when those disparities are hidden or not visible in the data being used. Fazelpour and Danks (2021) argue that algorithmic bias does not arise only from biased training data but can emerge at different stages of building and using an algorithm, such as how the problem is defined, how the model is designed, and how it is applied in practice. At each stage, human decisions can influence the results and may affect some groups more than others. They also point out that algorithms are not neutral tools, because they reflect the values and choices built into them, which can maintain or even deepen existing inequalities.

Research on user perception of AI systems shows that when users feel that there is no fairness, accountability, or transparency, their trust reduces drastically, and they become much less inclined to use AI-driven services (Shin, 2020).

Trust plays a central role in how users respond to biased or potentially unfair AI systems. Research indicates that concerns about discrimination, unclear accountability, and lack of recourse mechanisms significantly reduce users' willingness to trust AI technologies (Omrani et al., 2022). This suggests that when users perceive a system as unfair or opaque, their trust erodes with direct implications for platform engagement and acceptance of AI-driven recommendations.

The perceptions of fairness also differ in terms of culture and region. In some cultures, historical inequalities, local norms and expectations of justice influence the way people judge AI practices. A recent perspective article examining AI deployment in Africa suggests that the views of fairness of the users are influenced by social and historical contexts. Algorithmic bias can deepen concerns about unequal treatment, especially in areas like digital lending, where automated decision-making has already led to discriminatory results for marginalized communities (Pasipamire & Muroyiwa, 2024). These findings suggest that fairness is not a universal concept and it can be in the expectations of culture, social values and trust in institutions and there is no one standard fairness concept can fit in all markets. Given this, the ability to identify and mitigate algorithmic bias has become an essential organizational capability. Akter et al. (2023) suggests a dynamic capability framework comprising data, model, and deployment bias management capabilities, arguing that firms need integrated governance across all three dimensions to reduce unfair outcomes and protect customer equity.

In general, algorithmic fairness in digital market is shaped by the perceptions of fairness by users, the expectation of the cultures, and firm-level governance practices. However, algorithmic bias can undermine trust and weaken the acceptance of AI-driven services. Firms can address these risks by implementing transparent processes, algorithm audits, adapting fairness practices to local contexts, managing fairness as an ethical obligation for sustaining trust and ensuring long-term competitiveness.

2.3.3 Consumer Autonomy and AI-Driven Influence Across Digital Contexts

AI recommendation systems influence consumer decision-making by shaping the information environment in which choices occur. Such systems do not make a direct choice on behalf of users, but they guide attention through personalized navigation by displaying certain products, prioritizing algorithmic options that are available (Gao & Liu, 2023). These dynamics have been especially applicable in the context of the digital commerce, where design of platforms becomes central to the structuring of consumer choice architecture. From a philosophical perspective, Tiribelli (2024) argues that AI-driven systems act as “algorithmic choice-architectures” that reshape the environments in which consumers make decisions, not only reducing the diversity of options available to them but also gradually weakening their ability to critically reflect on and endorse their own choices over time.

Importantly, it is not the influence of recommendation systems that leads to lack of autonomy, but concerns about autonomy are raised when the users feel that their ability to make self-directed choices is being constrained. According to André et al. (2018), autonomy is experienced when individuals can freely select from various alternatives, which in turn fosters positive feelings and increases their motivation. Some users might feel discomfort or resistance in cases when recommendations seem to be overly customized or overly predictive, as accuracy seems to them as a threat to their autonomy rather than supportive (André et al., 2018), while consumers are generally unaware of the mechanisms behind these systems or the extent to which AI agents can be configured to shape their responses (Labrecque et al., 2024). Still, AI-generated suggestions can decrease the level of decision-making effort and increase convenience, which suggests that influence can be viewed as empowering or restricting, depending on how it is interpreted by users (André et al., 2018).

Because these interpretations are shaped by user's perceptions, transparency concerns become more critical when AI-driven recommendations are generated from data that was collected and inferred. In addition to explicit user inputs and directly observable behavioral data, AI-based systems can be based on implied knowledge based on patterns of interaction with the user. Although these inferred insights are not necessarily harmful, their invisibility can create uncertainty regarding the extent of information the system possesses and how such inferences affect the information it gives and shape the recommendations presented. As users feel that AI practices rely on the information that they have not provided with their knowledge, the feelings of unfairness or excessive impact can also occur. This concern is amplified by the limited visibility into how AI systems process information and arrive at specific outputs, making it difficult for users to assess the basis of the recommendations they receive, which is a factor closely linked to diminished trust (Omrani et al., 2022). These perceptions highlight the necessity of systems that increase the visibility of data use and provide users with greater control over the process of collecting and using their information. Taken together, the literature suggests that AI-driven influence operates through subtle adjustments to choice environments rather than explicit control over consumer decisions. The ethical implications for autonomy depend on how recommendation systems balance personalization with transparency and user control, particularly when consumers become more deeply embedded in AI-mediated environments.

2.3.4 Cultural and Market Contexts Shaping Ethical Perceptions

Cultural values and market contexts shape how consumers evaluate the acceptability of AI-enabled interactions in e-commerce, including their expectations about privacy, trust, fairness, and personalization. Mehmood et al. (2024) find that consumers across cultures generally recognize the convenience and relevance of AI-enabled personalization. However, the well-being concerns it provokes, such as intrusiveness, privacy erosion, and loss of autonomy, vary depending on cultural norms and values. These culturally contingent responses carry direct implications for how ethical boundaries of AI-driven personalization are perceived in e-commerce contexts. At a more localized level, Nugraha (2025) suggests that consumer evaluations of AI-based marketing personalization go beyond individual preferences to encompass social and relational dimensions, as assessments are shaped by social networks, collective experiences, and prevailing community norms. Yet privacy concerns remain a persistent barrier even among consumers with high brand trust, reinforcing the view that consumer responses to AI-driven personalization are embedded in everyday social contexts and shaped by cultural backgrounds.

The concept of trust becomes the key tool of connecting cultural values to the ethical evaluations of AI-driven systems. According to Hallikainen and Laukkanen (2018), national culture plays a major role in consumer trust in e-commerce as it affects consumer evaluation of competence, integrity, and benevolence of an online vendor. Recent cross-cultural research on AI-driven marketing further supports this perspective, Pasha (2025) examines consumers from two different cultural contexts, suggests that the association between AI-driven marketing and trust is mediated by cultural orientation. Individualistic consumers are more likely to focus on the control of their personal data, transparency and personalization, meanwhile, collectivist consumers are more sensitive to social approval and institutional trust. Based on survey evidence from Germany, Great Britain, and the United States, Kozyreva et al. (2021) find that while consumers are often relatively accepting of personalized services, they are much stricter about the collection and use of personal information that facilitates personalization, as respondents expressed stronger objections to the use of sensitive personal information even when AI-personalization outcomes were viewed positively. These findings suggest that data practices without transparency including the use of inferred data may lead to stronger ethical concerns than visible personalization features.

In addition to privacy, algorithmic bias represents a key ethical issue because it is closely associated with perceptions of fairness and legitimacy. Systematic review by Starke et al. (2022) shows that the perception of algorithmic fairness depends on both the outcome and the process of decision-making and the perception of bias can decrease the acceptance and trust in algorithmic systems. This is particularly important because fairness is not evaluated solely on technical grounds but through socially and culturally shaped expectations. Similarly, according to Pasipamire and Muroyiwa (2024), algorithmic bias may erode trust more strongly in contexts where institutional capacity is uneven and historical disadvantages are present. They emphasize the significance of inclusivity, cultural attentiveness, and local interaction in countering prejudice and gaining trust of AI systems. Even though they examine their issues within African settings, the implications are relevant for global digital businesses deploying standardized AI systems across culturally diverse markets.

Overall, the literature suggests that culture, trust, and privacy form an interconnected relationship in shaping ethical perceptions of AI in digital markets. The cultural context can shape underlying expectation about how data are used and what can be considered as an acceptable level of personalization; the gap between accepting personalized services and objecting to the underlying data collection highlights the role of transparency in shaping ethical perceptions; and the perceived bias in the algorithms can lead to unfairness and distrust. These differences across markets are therefore not incidental but represent an essential part of the ethical landscape that international e-commerce platforms must consider when designing and implementing AI-driven personalization and data practices.

2.3.5 Summary of Ethical Concerns and Relevance to the Study

Collectively, the studies reviewed from Sections 2.3.1 to 2.3.4 indicate that ethical challenges associated with AI-based e-commerce are complex and deeply interconnected. The combination of these works suggests that concerns related to data privacy and user consent are compounded by the lack of transparency in data processing and the general inferential powers of AI systems, particularly in situations where consumers are unaware of how their data is collected, processed, or compiled into new knowledge. These conditions create structural limitations to informed consent and affect the underlying ideas of trust and legitimacy in AI-based online systems.

The concern about algorithmic fairness extends the ethical evaluation of using data to other aspects of perceived validity and fairness of AI-generated results. Once the users feel that the algorithmic choices are prejudiced, obscure, or not sufficiently responsible, the trust in AI-driven services fades, which reduces the readiness to rely on automated suggestions and judgments. These perceptions have a consequence in the context of international business because they determine how AI-driven platforms will be received and trusted in particular markets, as opposed to being limited to individual user experiences.

The literature also indicates that AI-mediated personalization and recommendation processes influence consumer autonomy by structuring choice environments rather than removing choice altogether. Ethical concerns tend to arise when consumers perceive a loss of control, excessive personalization, or non-transparent use of data, even when AI systems enhance convenience and efficiency. These results emphasize that the reaction of the consumers to AI-based influence is highly subjective and situation-specific, as it is determined less by technical specifics on their own and more by the interpretation of personalization practices.

Importantly, these ethical concerns are not the same in different markets as cultural values, trust norms, and regulatory environments mediate how privacy, fairness, and autonomy are understood and prioritized. Cross-cultural evidence suggests that consumers in different market contexts apply distinct criteria when assessing the acceptability of AI-driven practices, indicating that ethical risks cannot be addressed through a single standardized understanding of acceptable AI use. Rather, consumer expectation differences is a core challenge for AI-enabled e-commerce that is being operated in different cultural settings.

In general, the literature suggests that ethical concerns in AI-based e-commerce emerge at intersections of data practices, algorithmic decision-making, consumer autonomy, and cultural settings. The above synthesis is highly relevant to the study, which examines the way in which consumers with diverse cultural backgrounds respond and interpret the ethical challenges in hyper-personalization, inferred data use, and algorithm bias in digital commerce. By explaining the ethical aspects identified in the previous research and its relevance to various markets, this section therefore provides a foundation for the study and outlines how participants' perceptions will be interpreted.

2.4 Synthesis and Conceptual Framework

2.4.1 Synthesis of Literature

The literature reviewed shows that AI-driven personalization in e-commerce should not be viewed merely as a technical development as it is also a multi-dimensional process, in which algorithmic systems interact with consumers' social values, cultural norms, and ethical expectations. As discussed in Sections 2.1 and 2.2, the impact of AI in digital commerce depends not only on how well algorithms perform, but it also depends on how consumers from different cultural backgrounds perceive and respond to AI-mediated interactions. Cultural context provides an important foundation for understanding why implementing the same AI practices can be accepted in some markets but it can also cause discomfort or concern in other contexts.

The ethical concerns synthesized in Section 2.3 highlight the complexity of these responses. The key themes we focus on, such as hyper-personalization, inferred data use, and algorithmic bias, appear as factors of both perceived benefit and ethical tension for consumers. Although AI-driven personalization is often viewed as a positive feature for its ability to improve convenience and relevance, the literature shows that these benefits frequently coexist with critical concerns about privacy, autonomy, and fairness. These ethical concerns are compounded with the question of consumer autonomy, because AI-driven personalization can affect the environment of choice and impact decision-making in ways that may not always be transparent or aligned with consumer intentions. Importantly, transparency does not operate as a simple mechanism that automatically increases consumers' willingness to share data. Prior research shows that transparency does not automatically encourage data disclosure, but it affects how consumers interpret AI practices, influencing their perceptions of legitimacy, control, and risk.

Through the reviewed studies, consumer evaluations of AI-driven practices are influenced by culturally grounded values including expectations about data control, acceptable levels of personalization, and trust in digital systems. In some cultural contexts, seamless experiences and efficiency are emphasized, while sensitivity to intrusiveness or extensive data use is more important in other contexts. For instance, Kozyreva et al. (2021) found that consumers in Germany tended to show lower acceptance of algorithmic personalization and data collection compared to those in Great Britain and the United States, despite reporting similarly high levels of privacy concern across all three countries. These cross-country differences indicate that consumer evaluations of AI-driven personalization may be shaped not only by technological characteristics, but also by broader contextual and cultural factors.

Although the reviewed literature shows the depth of cultural and ethical aspects of AI-driven e-commerce, there is still a gap remains in understanding how these aspects operate at the individual consumer level. While several studies have examined cultural differences in AI acceptance, there is limited research that explores the lived experiences and interpretive processes through which consumers from different cultural contexts evaluate the ethical aspects of hyper-personalization, inferred data use, and algorithmic bias. In response to this gap, the present study adopts a qualitative, consumer-centered approach to explore how consumers from different cultural backgrounds interpret and emotionally respond to AI-driven practices in e-commerce. By focusing on consumers' own perspectives and experiences, this research aims to deepen understanding of the relationship between culture, trust, and ethical perception in AI-mediated commerce, extending existing literature beyond system-level evaluations toward the lived experiences of users.

2.4.2 Conceptual Framework of the Study

Building on the comprehensive review of existing literature, this study proposes a conceptual framework to explore consumer perceptions of AI-driven practices in digital environment through different cultural contexts. The framework grounded in Cultural Dimensions Theory and Trust Theory, and also referenced Responsible AI Principles. The Figure 1. presents the four-phase model guiding this research.

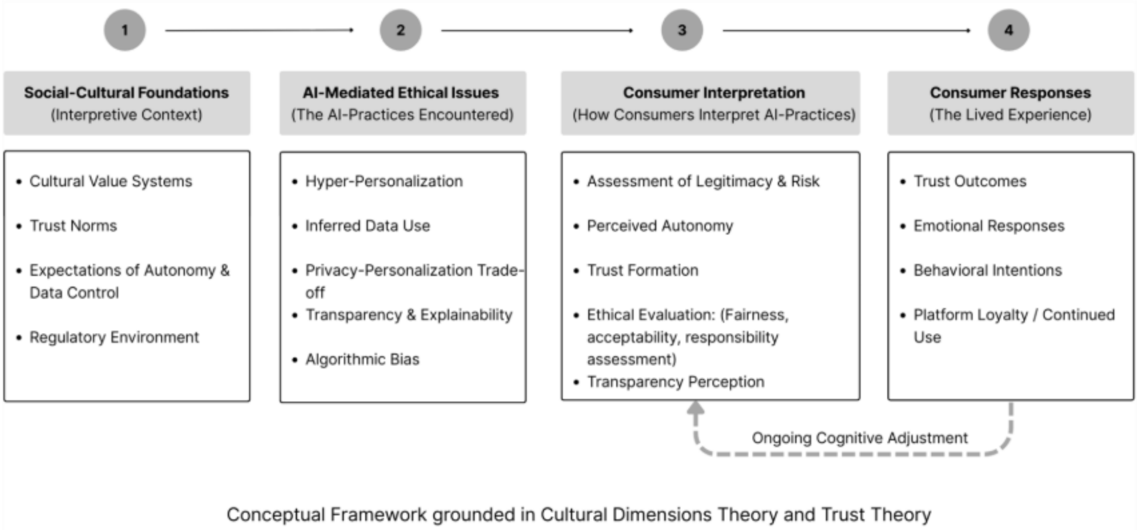

Figure 1. Conceptual Framework for the study

The framework explains the consumer experience journey beginning with the original social-cultural setting to the end lived experience in four interconnected phases:

Phase 1 (Social-Cultural Foundations) determines the existing interpretive context. It includes cultural value systems, contextual trust norms, expectations of agency, and the regulatory environment. These elements form the baseline expectations that consumers bring to their digital interactions before the technological encounter occurs.

Phase 2 (AI-Mediated Ethical Issues) identifies the salient ethical dimensions emerging from specific AI practices. These include hyper-personalization, inferred data use, privacy-personalization trade-offs, transparency and explainability, and algorithmic fairness. These issues serve as the primary stimuli that trigger ethical evaluation.

Phase 3 (Consumer Interpretations) is the core interpretive process in which consumers make sense of the identified issues. This involves an assessment of legitimacy and risk, evaluation of perceived autonomy, and trust formation. During this phase, consumers utilize Responsible AI Principles as normative benchmarks to decode the ethicality of the platform's behavior.

Phase 4 (Consumer Responses) represents the multi-dimensional outcomes of the "lived experience". These include dynamic trust states (reinforcement or erosion), affective responses (emotional and ethical tension), and behavioral intentions such as platform loyalty or resistance. The dotted arrow represents ongoing cognitive adjustment, acknowledging that these lived experiences continuously update and refine the consumer's future interpretations and evaluations.

The integration of these theoretical lenses allows the study to explain why consumer perceptions vary across markets (via Cultural Dimensions) and also explain which specific ethical dimensions resonate most with users (via Trust Theory and AI Principles). This framework addresses the research questions by exploring how consumers from diverse cultural backgrounds (Phase 1) perceive and navigate AI-mediated ethical issues (Phase 2) through their own interpretive processes (Phase 3), resulting in varied lived experiences (Phase 4).

3 Methodology

This chapter presents the methodology applied in this thesis. It begins with the research philosophy and research approach, followed by a description of the research process, data collection method, and data analysis method. The chapter also addresses ethical considerations, limitations, and the validity and reliability of the findings.

3.1 Research Philosophy

The thesis applies the interpretivist research philosophy. With the aim to explore consumer's perceptions, we seek to understand how individuals from different cultural backgrounds interpret AI-driven practices in e-commerce by their own views, interactions, expectations and experiences. Interpretivism emphasizes that humans are different from physical phenomena because they create meanings, and as individuals from different cultural backgrounds make different meanings, they construct and experience different social realities (Saunders et al., 2023). The interpretivist paradigm therefore attempts to formulate detailed, subjective understandings of human behavior and interactions (Saunders et al., 2023).

Although AI-driven systems represent technological advancements, the thesis does not examine them as specialized tools. Rather, we are seeking to explore the interaction between these systems and the way in which their practices affect human perceptions. Interactions between consumers and AI systems are socially embedded practices and influenced by cultural, prior experiences, contextual interpretations, and these technologies can be perceived and evaluated differently by individuals from different contexts. As interpretivist research allows researcher understand deeply in social realities, acknowledging that interpretations of what may appear to be the same phenomenon can vary across cultural and geographical settings (Saunders et al., 2023), it is suitable approach for this thesis for the research to capture nuanced particular comprehensions cannot be fully captured by numerical data alone.

This philosophical stance is associated with the qualitative research methodology because it is based on interpretivist assumptions and it allows researchers to engage with subjective and socially constructed meanings (Saunders et al., 2023). This method is more appropriate to investigate the perception and interpretations of the participants regarding ethical concerns in AI-driven e-commerce.

3.2 Research Approach

In the thesis, an abductive research approach is chosen as it allows researchers to move iteratively between existing theories and data, making comparison and interpretation (Saunders et al., 2023; Dubois & Gadde, 2002). Dubois and Gadde (2002) refer to this iterative process as systematic combining, an approach particularly suited to exploratory studies where existing theoretical frameworks provide a starting point but do not fully explain the phenomenon under investigation. In this way, abductive theory development is open and sensitive to data, and at the same time it uses theories as a source of inspiration for identifying and interpreting patterns (Saunders et al., 2023). Since existing theoretical perspectives are used as analytical lenses for interpreting the findings, this approach allows researchers to facilitate a reflective engagement between theory and empirical data (Van Maanen et al., 2007). It supports a deeper understanding of how consumers construct ethical judgments about AI-driven practices while remaining open to interpretations that may not be entirely explained by established theoretical perspectives.

3.3 Research Process

The thesis follows a qualitative research method to explore how consumers perceive and interpret AI-driven practices in e-commerce. The research process starts with the development of a semi-structured interview guide based on the objectives of the study. As the research seeks to investigate consumer perceptions, semi-structured interview is considered an appropriate way to conduct the research (Saunders et al., 2023). Interview questions are designed in an open-ended format, this encourages participants to expand on their responses and allows a more thorough understanding of their personal experiences and viewpoints (Saunders et al., 2023). The questions will center on the experience of participants in using AI-driven personalization, how they view practice of inferred data, their perceptions of fairness in algorithm and their perceptions of trust and autonomy when they interact with e-commerce platforms.

3.4 Data Collection

Interview Design

The empirical data is collected through semi-structured interviews. In this format, an interview guide is used to outline the key topics of interest while still focus the subjective experiences and attitudes the participants so that all the important themes are covered and the participants are given a chance to provide their personal views (Krishnaswami & Satyaprasad, 2010. However, there are participants who are unable to attend live sessions because of time zone differences and other scheduling constraints, so we choose asynchronous written interviews as an alternative to accommodate this. These participants receive the same semi-structured interview questions and they are requested to give detailed written answers. The follow-up questions are then sent to seek clarification or further explanation of their answers. This approach helps preserve the interactive and exploratory quality of semi-structured interview, even though communication does not occur in the real time (Dahlin, 2021; Meho, 2006). Using a mixed mode interviewing strategy is recommended in qualitative research, especially when time or geographical constraints make real-time interaction difficult (Meho, 2006).

Sampling Strategy and Participant Selection

A purposive sampling strategy is used to choose participants who could provide relevant meaningful insights in relation to the research focus, particularly participants from different national and cultural contexts. This sampling approach involves choosing participants according to specific, pre-established criteria that align with the aims of the study (Krishnaswami & Satyaprasad, 2010). When selecting participant from different culture contexts, as we aim to balance diversity of perspectives with depth of insight, we chose some participants who can give reflective and descriptive accounts of their encounters with AI-driven systems so that their familiarity with digital environments or experience related to technology allows them to articulate nuanced views on the issues concerned. At the same time, we also included participants from non-technical backgrounds so that the collected data would incorporate different interpretations and experiences. We select the participants based on three main criteria their cultural background, their experiences using digital online platforms so their reflections are grounded in actual consumer experiences, and their familiarities with AI-driven features such as personalized recommendations or algorithm-based suggestions so that they can discuss their perspectives and their personal interactions with these systems.

The final sample involves 10 participants and they are selected in different age groups, ranging from 20-29 to 50+. The sample distribution aimed to include diverse perspectives from different cultural backgrounds. The sample is not intended to represent each country statistically.

Table 1 below provides information of the 10 participants including the country of origin, country of residence, age range, occupation and technical background. Each participant is identified by a designated code.

Table 1. Participants' profiles

No	Country of Origin	Country of Residence	Age Range	Occupation	Technical Background
VN1	Vietnam	Finland	40-49	Civil Engineer	Technical
VN2	Vietnam	Vietnam	59+	Home maker	Non-Technical
VN3	Vietnam	Vietnam	59+	University lecturer	Non-Technical
IND1	India	Finland	30-39	Mechanical Technician	Technical
US1	USA	USA	20-29	Software Engineer	Technical
US3	USA	USA	30-39	Analyst	Technical
US4	USA	USA	30-39	Student	Non-Technical
CA1	Vietnam	Canada	30-39	Service Technician	Technical
NE1	Nepal	USA	20-29	Student	Non-Technical
FI1	Finland	Finland	20-29	Receptionist	Non-Technical

Interview Procedure

The interviews are conducted using face-to-face, synchronous online, and asynchronous written formats because participants are located in different regions. The language used in most of the interviews is English. However, as not all participants are fluent in English, some of the interviews are conducted in the native languages, so that the participants can describe their experiences and views to their full extent and in a natural way. Conducting interviews in participants' native languages is considered essential because conducting an interview in English may cut the linkage between language and cultural identity, which would leave non-English speaking participants at a disadvantage and blur the nuanced meanings embedded in their lived experiences (Temple & Young, 2004). The interviews are audio-recorded with the participants’ consent and the interviews conducted in languages other than English are then transcribed and translated into English for the purpose of thesis analysis and reporting. For asynchronous written interviews, the written responses serve as the primary data record and responses in languages other than English are translated into English following the same translation procedures. As most participants request anonymity, all personal identifiers are removed from the transcripts and reporting for their confidentiality and data protection.

Ethical Considerations

The research is conducted in accordance with established ethical principles for qualitative research with human participants. All participants are informed about the study and given the informed consent forms before starting the interviews to ensure that their participation is entirely voluntary and free from coercion (Saunders et al., 2023). Participants are informed that they can withdraw from the research at any time and any of their data collected up to that point would not be used. There are interviews conducted in participants’ native languages, this is not because of language barriers, but to allow them to comfortably share their experiences and perspectives in more details and increase the depth and richness of the qualitative data.

In qualitative interview-based research, ethical considerations extend beyond standard requirements such as anonymity and data storage to include the ongoing wellbeing of participants (Husband, 2020). To protect participant privacy, all identifying information is eliminated in the interview transcripts and in the presentation of the results. Only the researchers can access raw data, and all the materials are secured and stored in line with the principles of data protection. Audio recordings are used solely for transcription and analysis purposes and translated transcripts are handled carefully to preserve the original meaning without leaving any identifying information. Written responses from asynchronous interviews are kept confidential and securely stored with the interview transcripts.

3.5 Data Analysis

The data collected from the participants is analyzed using Thematic Analysis that follows 6 phases framework developed by Braun and Clarke (2006). The approach is aligned with the interpretivist research philosophy because it allows researchers to explore various interpretations of a phenomenon (Saunders et al., 2023). We start the analysis by reading through all transcripts multiple times to develop a thorough understanding of the data. The interviews conducted in participants' native languages are transcribed and initially coded in original languages to maintain the contextual meaning, then translation into English is conducted at the stage of reporting and presentation of findings to ensure that thematic interpretation remains grounded in the original data. During this familiarization phase, we write down our initial observations and impressions while reading the transcripts to help guide the coding process in the next step.

In the second phase, we organize the data by identifying parts of the transcripts that relate to the research questions and assigning them initial codes. The coding process combines In Vivo Coding, which uses participants’ own words as codes to retain their original voice, and Process Coding, which applies gerunds to capture the actions and responses described in the data (Saldaña, 2021). The coding process is conducted manually by both researchers to maintain close engagement with the data and to ensure contextual sensitivity. The codes are subsequently reviewed with larger patterns and combined into preliminary themes. The grouping of the codes into the themes is guided by the empirical data and the theoretical lenses applied in the study. This shows the nature of the abductive research, as themes develop through a continuous interaction between the data and relevant theoretical concepts (Saunders et al., 2023). At this stage, the preliminary themes are carefully reviewed to ensure that the data within each theme is logically consistent and that each theme is clearly distinct from the others (Braun & Clarke, 2006). Broader themes can be divided into sub-themes and overlapping themes can be merged. The themes are examined through the theoretical lenses outlined in Section 2.2, allowing a reflective interaction between empirical findings and existing concepts. Each refined theme is clearly defined to explain its focus, key features, and relevance to the research questions. A descriptive and meaningful name is assigned to each theme to accurately reflect the central idea emerging from the data. In the final phase, the identified themes are woven into a structured narrative that shows how they relate to each other and address the research objectives. There are relevant quotations extracted from the interview data are used to highlight and reinforce the key themes emerging from the analysis. (Braun & Clarke, 2006).

Although the six phases are outlined in a sequential order, the analysis is cyclical and iterative rather than strictly linear (Braun & Clarke, 2006). The theoretical lenses function as sensitizing concepts as they provide a general direction for the analysis rather than imposing predetermined categories on the data (Blumer, 1954, as cited in Bowen, 2006). This enables the researchers to identify patterns that are theoretically meaningful while remaining receptive to novel insights from participants.

3.6 Limitations in Data Collection and Analysis

The thesis has several limitations that we acknowledge. First, as we work with a small sample of 10 participants, this sample size may limit the range of perspectives represented in the research. Although this sample size suits qualitative research that prioritizes depth, it has limitations to greater capture the diversity of experiences across different cultural backgrounds that this research aims to investigate. Second, as we conduct the interviews using face-to-face, synchronous online, and asynchronous written formats, these different interview modes may have influenced how participants engaged with the interview that may result in some variation in the data. There are also some participants who did not answer follow-up queries and therefore restricts the depth of their response and contribution. In addition, several interviews are conducted in participants' native languages and later translated into English for analysis. Although we carefully preserve the original meaning during translation, it is difficult to completely avoid subtle shifts in nuance or culturally embedded expressions during the translation process.

These limitations suggest opportunities for future research to increase the sample size, include a more diverse range of participants, apply a standard interview format to enhance comparability, and further optimize the cross-language data collection and translation mechanisms to increase the strength of analytical rigor.

3.7 Validity and Reliability

In qualitative studies, reliability and validity must be preserved to guarantee the credibility and trustworthiness of the results (Saunders et al., 2023). Reliability is the consistency and reproducibility of the research process, whereas validity is the accuracy of findings in representing what the research aims to investigate. Because qualitative research is based on interpretation and not statistical measurement, this research uses the concept of trustworthiness suggested by Lincoln and Guba (1985) that includes credibility, transferability, dependability, and confirmability. Even though qualitative research does not seek statistical generalization, the research context and the profiles of the participants are described in-depth to allow readers to determine the relevance of the results to other analogous contexts. To increase reliability, the present study is based on a semi-structured interviewing procedure and thematic analysis. Furthermore, a peer debriefing process is conducted between the two researchers in the team, who frequently engage in discussion and compare their interpretations of the data to detect possible biases and reinforce the analytical rigor. Additionally, reflexivity is maintained throughout the research process. The research team includes one Vietnamese and one Nepalese researcher, both interviewing participants from their own countries. As cultural familiarity may also lead to biased interpretation, the researchers regularly compare their interpretations from their different perspectives to reduce this risk.

4 Empirical Results

This chapter presents and examines the empirical findings. The interviews were conducted to explore the participants' experiences with AI-driven personalization, inferred data, and algorithmic bias in the e-commerce. The four themes identified from the data, as outlined in the following sections, analyze consumer perceptions and reactions to these practices. As the sample represents individuals from diverse cultural contexts rather than cultural populations, cultural dimensions are not treated as a primary analytical category but as an interpretive backdrop that surfaces through participants' expressions, metaphors, and boundary-setting across themes.

4.1 Experiencing AI-Driven Personalization and Inferred Data

Across participants, AI-driven personalization was experienced as both beneficial and, at times, uncomfortable, with most participants not responding to it in a definitive way but having a complex attitude toward it. What emerges from the interviews is a recurring pattern where the very characteristics that make recommendations useful, their relevance and accuracy, can also make the underlying system more visible and, in some cases, intrusive or uncomfortable. This tension seemed to be enhanced when participants perceived that platforms are making inferences beyond what they had willingly provided.

Participants were generally aware of the functional value of personalized recommendations. Several described them as reducing search effort, supporting product discovery, simplifying the process and making online shopping more convenient. VN2, for example, appreciated that personalization was “convenient for me, giving me more options to choose from and making it easier to compare prices*”* while US1 described it as “part of the online shopping experience.” IND1 also highlighted its usefulness in a more task-oriented context, noting that it helped him “get more idea to improve more my work” when searching for specialized items.

The positive experience did not end at functionality, as revealed by some of the participants through relational interpretations. Several Vietnamese participants described AI-driven recommendations in ways that resembled familiar seller-customer interactions. VN3 explained that “If you go shopping and you meet a seller understands what you want, that is a wonderful experience. E-commerce seem to be able to do this.” Similarly, VN2 described AI as something closer to domestic support than commercial targeting:

> *“I see AI on shopping platforms like a small assistant. It reminds me of items I usually buy, alerts me when things may run out, or suggests suitable products. It feels like someone helping me take care of my household.” (VN2)*

These descriptions indicate that personalization can be perceived as attentive service in certain settings, rather than merely a technical system, especially where it blends into normal day-to-day activities.

Nonetheless, the accuracy that makes personalization useful is also the factor that promotes a heightened awareness of tracking. VN1 observed that recommendations were useful because they “save time and help me find related items more easily” but also “remind me that the system is tracking my browsing behavior quite closely”. Similarly, US3 summarized this duality succinctly:

> *“It’s both intrusive and convenient at the same time.” (US3)*

A similar sense of ambivalence was reported by US4, who said that recommendations appeared “weird”, but she was “getting used to it” as AI becomes more pervasively used. This was furthered by NE1 who described personalized suggestions as both useful and insecure, which implies that the experience may move beyond discomfort to a feeling of insecurity. Participants did not reject personalization outright, they seemed to tend to accept this tension as a component of the wider online environment.

Notably, personalization also created discomfort when it was highly accurate yet failed to reflect the user's actual intentions. IND1 described a situation when he searched for the items on behalf of others, after which he was exposed to persistent and irrelevant recommendations that did not align with his own preferences:

> *"Sometimes we search for someone else, not us, and next time when we come to the platform and it keeps showing the items that we don't need… it is wasting my screen and time for searching and make me miss other options… those similar items keep coming to my screen and I cannot remove it." (IND1)*

He also said that under these circumstances, he would prefer to completely opt out of personalization:

> *"If I have to compare the feeling when those personalization go wrong to me, I prefer to be fresh user." (IND1)*

This description reveals a limitation of personalization systems, which is that they can interpret temporary or context-dependent behavior as a lasting preference, creating a profile that does not actually represent the needs of the user anymore. In those situations, irrelevance is not the only problem, but also a perceived lack of control because users have limited ability to correct or reset those system's assumptions. A similar distinction was made by FI1, who found that recommendations based on explicit product features (such as color or pattern) were useful, whereas less explicit types of suggestion did not appear to be meaningful. All these descriptions imply that personalization can cause uneasiness in both ways, when it is highly accurate and shows tracking, and when it is inaccurate and limits relevance.

The discomfort intensified when participants perceived that platforms were extracting information that they had not intentionally shared. Participants described experiences that they interpreted as the system using unintended or less visible data sources. IND1 also described a situation in which he had privately discussed travel plans, and later he had encountered related advertisements online which made him feel unsettled:

> *"I feel really weird and this is like no privacy even in bedroom." (IND1)*

US3 also talked about instances in which he had been discussing a product and then and then saw it recommended to him, which he found this "concerning". US4 theorized that it was possible data connections were being made through social networks: "I have this other person's phone number. So maybe they're connecting like what they're searching into what I'm like." This implies that consumers actively formulate explanations of uncanny targeting, trying to identify a rational process behind experiences that otherwise seem inexplicable. VN2 linked these experiences to microphone permissions granted during registration while FI1 expressed discomfort with data appearing to move across platforms, describing this as "creepy". These descriptions indicate that personalization is even more concerning when it is seen to go beyond observable user actions into inferences that are less transparent and less deliberate in the eyes of the user.

In some cases, participant's sustained exposure to highly personalized recommendation resulted in a sense of fatigue rather than continued appreciation. VN2 described this explicitly:

> *"When suggestions are too many and too accurate, I feel a bit tired - like being 'led' too much." (VN2)*

VN1 was also suspicious that many of the recommendations were "paid advertisements", and US3 mentioned that when too many suggestions are made it may cause "choice paralysis". These responses suggest that personalization may reach a point of diminishing returns, where increased relevance does not necessarily improve the experience, but instead reduces diversity, spontaneity, or the sense of independent choice.

Cross-cultural insights

Some Vietnamese participants conceptualized personalization in terms of relational metaphors, that is, being “known” by a platform could be linked to good service. The American participants showed a broader range of responses, from normalization (US1) to explicit ambivalence and concern (US3, US4). NE1, relying on experience in various cultural settings, expressed both usefulness and insecurity, showing a more visibly conflicted assessment. However, strong reactions to inferred data were present across participants of all cultures, especially in situations that dealt with perceived access to private conversations. This indicates that discomfort might not be dictated so much by nationality itself but more by the kind of data being inferred and the degree to which it seems to transcend personal boundaries.

4.2 Data Collection, Normalization, and the Limits of Acceptance

Although all participants acknowledged platforms monitoring their actions, most participants reported a gradual process of normalization where data collection became anticipated and a largely taken-for-granted aspect of digital environment. Participants continued using platforms not because they were unconcerned about data collection practices, but because participation had become normalized and, in many cases, difficult to avoid due to structural conditions. Awareness of tracking was universal throughout the sample, but what varied was the level of emotional response and the extent to which this awareness translated into action. Several participants saw data collection as something they were used to. US1 described it as a mere “part of the online shopping experience” whereas US4 noted that she was “getting used to it”. FI1 observed that personalized results “happen so often already, we don’t always notice” suggesting that, by repetition, algorithmic personalization had become an element of the background of digital life rather than something that prompted active evaluation.

US3, however, described a more critical awareness of this process, using a metaphor of gradual accumulation of data collection as a process of slow conditioning: “Little steps, little chunks of data, more and more, until it builds up… Boil the frog slowly and it doesn't realize it’s being cooked.” Interestingly, US3 was the only participant who reported attempting to cut down his online shopping habit due to this awareness, specifically saying that he attempts “not to shop online as much anymore because of that reason.” His explanation is that although normalization might proceed unnoticed for most consumers, being aware of the trend does not necessarily make it easy to reverse.

US3 further contextualized this normalization as a broader cultural reversal, recalling that early internet culture had a fundamentally different orientation toward personal data:

> *“They used to back in the day, when the internet was young. Everyone said ‘Never use your real name, never upload anything, the internet is forever, don't care personal details, don’t give out information.’ Now everyone does it willingly, the culture is totally backwards. Edward Snowden revealing the capabilities of the government, Palantir creating profiles on citizens, data brokers selling your data and your profiles, traffic cameras scanning license plates, ring cameras tracking and sharing data.” (US3)*

For US3, these examples formed an interconnected surveillance landscape that shaped how he evaluated e-commerce data practices not as isolated commercial activity but as parts of a broader system of data collection. This awareness made him “way more cautious” and expressed a desire to eventually “detach from everything” representing the most extreme response to normalization in the sample.

The pattern that kept recurring in interviews was the discrepancy between the privacy concerns participants stated and their continued platform use. NE1 made a comparison to sustainability behavior:

"People act like they care about the sustainability but they couldn't control themselves by buying the cloth things. Same applies here too." (NE1)

US3 was more precise in quantifying this tension by indicating that "convenience and price will 90% of the time outweigh any moral stance or convictions". VN3 also shared this feeling of acceptance by saying that "the more we shop online, the more our information are stored. We have to understand and accept that." Collectively, these narratives imply that concerns about privacy do not necessarily translate into behavior change, especially where the level of convenience and perceived advantages is high.
However, when the privacy-for-benefit trade-off was made explicit during the interviews, almost all the participants declined. VN2 articulated her refusal through an expression:

"I always think that anything free only exists in a mousetrap. Moreover, it would bring more trouble than benefits." (VN2)

US3 mentioned that he would "rather pay more than feed more data into some algorithm or tech broker", and IND1 added that if he had to provide information, he would intentionally provide false information. CA1 maintained that he does not "give out any more information than what is absolute bare necessity". This gap between ordinary tolerance of data collection and direct rejection of trade-offs implies that the framing of the exchange matters as much as the exchange itself and people may tolerate data practices that operate in the background but resist when they are required to explicitly extend their involvement.

Although the overall trend was towards normalization, participants used different resistance strategies. CA1 described ad-blocking as "sadly a must-have add-on these days". IND1 had been using VPN and IP switching to avoid location-based tracking and reported providing false information when required to share his personal information. VN2 described a community practice of using a different phone number for online shopping, representing a collective and culturally ingrained form of resistance. US3

reported deliberately reducing online shopping, and IND1 described physically removing smart devices from private spaces during sensitive conversations.
Nevertheless, these resistance efforts were often limited by structural dependency on the platforms themselves. NE1 recognised this tension directly:

> *“I can’t say that I’m not gonna use those services again because we have to use it.” (NE1)*

US4 identified the elimination of non-digital options, noting that “a lot of places don’t take cash” as a structural factor that diminishes consumer choice regarding participation in data-collecting systems in the first place.

Cross-cultural insights

The degree to which data practices were discussed also seemed to vary across participants from different cultural backgrounds. Indian and Nepalese participants referred to their communities as largely unaware or indifferent, IND1 reported that “people normally don't care much about these or they are not aware”, and NE1 said that “they don't care about the privacy”. Vietnamese participants described awareness without deep discussion, VN2 talked about knowing that people around her were being tracked but they do not discuss how AI systems actually operate, whereas VN3 framed data collection practices as a common business practice, and even imagined that stored personal information might result in a pleasant surprise such as a birthday discount. Among the American participants, US3 explained that there was a social stigma around raising privacy concerns, noting that “you'd sound like a conspiracy theorist”. FI1, by contrast, described cybersecurity as "a common topic of conversation" in Finland. Such observations indicate a spectrum of privacy discourse, ranging from largely absent to actively normalized, which seems to be shaped by the wider social and communicative context in which the participants live.

4.3 Consumer Autonomy, Algorithmic Influence, and the Opacity of AI-Driven Systems

One of the most prominent trends presented in the data was a repeated tension between the participants expressing their belief in their free choice and the narratives of their being subtly influenced by algorithmic systems. To some degree this tension seems to be perpetuated by the opacity of AI-driven systems, when consumers do not understand how systems are influencing their decisions, they are less able to judge or object to that influence. All these dynamics tend to imply a kind of autonomy paradox in which consumers' belief in their own independent decision-making coexists with forms of algorithmic steering that can take place beyond consumers' immediate awareness.

The discrepancy between self-assessed autonomy and described susceptibility was found in multiple participants. VN1 stated that he "chooses freely" and "usually knows what to buy before browsing", yet elsewhere in the interview acknowledged that "when a product appears at the top of the page or is marked as recommended or popular, I tend to pay more attention to it". IND1 claimed that "AI can't influence me much because I know it well" but later he admitted that "I can feel it pushes to a certain direction and I don't really like it". NE1 captured this tension most explicitly:

> *"I cannot say that it's I can choose the item freely. It seems like that I can choose freely, but the AI things influence a lot and then I keep scrolling so many things at the same time." (NE1)*

NE1 also narrated a specific case in which she intended to purchase a particular item but once she saw jewelry recommendations appear prominently, she "randomly" purchased the recommended items, which showed the gap between the intention to resist and the reality of the interaction. US1 showed another form of this tension: she admitted that AI "somewhat limits our browsing habits, which may hurt new and small businesses" but still said that she "never feels pushed in a certain direction". Instead of contradicting herself, US1 attempted to re-contextualize the limitation as "optimization" rather than a restriction on her autonomy. This suggested that how consumers label algorithmic influence may determine whether they perceive it as a problem.

The participants explained that the influence operated at various levels, some of which were quite apparent and others that were more subtle and difficult for participants to recognize or resist. On the most apparent level, VN1 described the influence of positional prominence, where products at the top of the search results or labeled as "recommended" or "popular" received a disproportionate level of attention. VN2 recognized urgency and scarcity tactics like "only 2 left" and "50 people viewing", but she did not feel pressured as she consciously dismissed them by reasoning that limited stock did not necessarily mean she should buy, since she could not exchange defective items, and that high viewer counts did not actually mean that people were buying. US4 mentioned the persistence of repeated recommendations, where suggestions to purchase dog name tags were still visible even after buying them once.

On top of these surface-level mechanisms, a few participants also talked about influence operating at the level of desire formation itself. US4 traced a specific pathway in which exposure to fitness-related content on Instagram resulted in advertisements for athletic wear, which gradually created a sense of need:

> *"Very subtly, yes, I think it does. There's a point that I'm like, oh, I do need this thing as well. I need this item to go with my workout." (US4)*

US3 extended this observation to a systemic level, identifying "entire cultures/memes/followings being created around certain products that may or may not be authentic", and questioned whether consumer demand itself is partly manufactured. VN2 described recommendations as generating needs that were not already present, desires that would not have arisen without algorithmic intervention. These descriptions imply that algorithmic influence may extend beyond shaping which products consumers choose to influencing what consumers come to perceive as needs.

Beyond these observable mechanisms, the accounts of participants also pointed to a deeper structural issue, the opacity of platform data practices. Such types of influence seemed to be perpetuated, in part, by the limited visibility consumers have into how platforms gather and use their information. When asked about platform transparency, no participant reported having fully read a privacy policy on any online platform. The barriers cited were consistent: VN2 described them as “long, written in legal language, and not user-friendly,” whereas US1 dismissed them as “too long, never read” and CA1 mentioned that he assumes “everyone does the same”. IND1 viewed privacy policies as a form of legal protection rather than genuine transparency, characterizing them as existing “just for clearing their legal side”, implying that platforms disclose data practices primarily to shield themselves from legal liability, likely because regulations require them to, rather than out of any commitment to informing users. FI1 went further, perceiving the vagueness as strategic:

> *“Terms and conditions are often vague on purpose*.*” (FI1)*

These responses suggest that the information infrastructure intended to support informed decision-making is, in practice, largely inaccessible to users, creating conditions in which algorithmic influence operates without meaningful consumer oversight.

More notably, when asked whether clearer explanations of data practices would increase their comfort, some participants indicated that transparency could have an unsettling effect. VN2 stated:

> *“If they explained in too much detail how they use personal data, I might feel more worried than reassured, because I would realize they are tracking and analyzing me more than I thought’’ (VN2)*

IND1 expressed a similar concern, noting that transparency regarding data collection for sensitive purchases like gold could leave people with a sense of insecurity instead of confidence. These responses point to a transparency paradox: consumers do not have the information required to evaluate how platforms influence their choices, yet detailed disclosure may increase anxiety rather than empowerment. This leads to a situation where influence and opacity become mutually reinforcing, consumers are not able to resist what they cannot see, and seeing may itself be unsettling.

Some participants described deliberate counter-strategies, though these appeared to operate primarily at the surface level of algorithmic influence. VN2 had a discipline of purchasing “what I need, not what I like” actively resisting any suggestions that were not based on practical necessity. CA1 reported always knowing what he intended to purchase before visiting any shopping platform. VN3 and FI1 anchored their decisions to budget constraints, whereas US4 noted that having more time to conduct research reduced her susceptibility to algorithmic defaults. However, none of the participants described strategies for countering the deeper level of influence, the formation of desires and perceived needs through algorithmic content curation.

The aggregate of these findings indicates that the autonomy of consumers was commonly upheld at the level of self-perception, despite their accounts showing that their experience was influenced in many different ways by subtle algorithmic steering. This dynamic seemed to be compounded by the opacity of platform practices: consumers could not fully evaluate how their choices were being shaped, and the prospect of greater transparency did not consistently promise greater empowerment.

Cross-cultural insights

The paradox of autonomy was manifested in all the cultural groups, but it was described differently by the participants. Vietnamese participants were more likely to use pragmatic counter strategies - prioritizing needs over wants (VN2) and budget anchoring (VN3) - without presenting the problem as a concern about rights or personal freedom.

Among the American participants, US1 perceived no influence at all and reframed algorithmic limitation as optimization, while US3 described a systemic problem extending beyond product recommendations to the manufacture of cultural trends. The contrast between intention and action is demonstrated in NE1's admission of impulse buying in spite of her conscious resistance. In terms of the awareness of opacity, participants from India and Nepal indicated that those surrounding them were generally unaware of how data practices operate, whereas FI1 reported an active culture of cybersecurity awareness in Finland. The participants from Canada and India both reported strong autonomy through pre-research and technical knowledge, respectively.

4.4 Conditional Trust, Perceived Fairness, and the Boundaries of Acceptance

Trust was rarely expressed as absolute; instead, it was usually described as conditional, context-dependent, and sustained through verification or practical boundaries. This theme explores the conditions under which consumers placed trust in AI-driven systems, their perceptions of algorithmic fairness, and the lines they drew between acceptable and unacceptable platform behavior. Where participants quantified their trust, it fell in the moderate-to-low range: US4 rated her trust at three to four out of ten, IND1 at four out of ten and NE1 at five out of ten. Two outliers emerged at the opposite ends: VN2 expressed zero trust, citing awareness of "many cases of massive data leaks", and US1 expressed full trust, noting simply that AI systems have been a convenience.

Two broad trust orientations appeared across the sample. The first was outcome-based: trust was determined by whether the system delivered useful and relevant results. VN1 stated that "what matters more is whether the recommendations are useful and whether the platform works conveniently", and CA1 described AI as "just another source of information" that he always cross-checks. The second orientation was process-based: trust required some understanding of how the system operates. US3 articulated this through a metaphor:

> *"AI can be a useful tool, and I'll trust the tool for what I use it for. I wouldn't trust my handsaw to make a sandwich. When data/algorithms get shared and are let out of the box, that's when I no longer trust it." (US3)*

FI1 similarly valued knowing "what actually happens", whereas NE1 emphasized that companies "must be transparent" when it comes to their use of data. A third orientation was found in the account of CA1, where trust was not based on the platform's outputs or processes but on the institutional infrastructure surrounding it:

> *"Here in Canada, I say most people have a higher level of trust in online shopping website like Amazon, because the consumer protection laws are fairly robust and enforced properly." (CA1)*

For CA1, trust appeared to rest less on the reliability or transparency of the AI system itself, and more on whether the regulatory environment provided sufficient protection against negative outcomes. Some participants exhibited elements of both orientations, VN2 valued AI's functional helpfulness, referring to it as a "powerful supporter" while simultaneously expressing zero institutional trust. Across most participants, the most prevalent practice was trust-but-verify: VN3 described always cross-checking information before making a final decision, VN1 compared options across platforms, and VN2 treated AI recommendations as "reference only, not something to rely on completely". Notably, as discussed in the preceding theme, the opacity of platform data practices appeared to shape how trust was formed: when consumers did not understand how the systems operate, trust formation appeared to shift away from informed evaluation of processes and toward reliance on perceived outcomes and practical experience.

Several participants described experiences suggesting that AI-driven platforms may treat users differently depending on their location, browsing history or device. VN2 discovered that one of her friends had a lower price for the same flight, which she described as feeling "treated differently and not completely fairly". This was systematically tested by IND1 by switching devices and VPN locations, confirming that prices differed:

> *"I think in the case of flight ticket price it is not really fair, price should be globalized. But because I know how to search, so it doesn't bother me much." (IND1)*

NE1 found a lower price for the same product on a different platform on her husband's phone, VN1 observed higher shipping costs and fewer choices when he was shopping from Finland and noted that "even if the system is not intentionally unfair, the results may still be different for different people." US4 sensed that AI is "breeding into bias, possibly." Interestingly, VN3 expressed more accepting view, stating that "high-end products for people with more money and lower-end products for people with less money are reasonable business rules", and "you get what you pay for". For VN3, economic segmentation by AI systems appeared to reflect normal market principles rather than algorithmic unfairness. US1 offered a similar but differently framed perspective, reframing differential treatment as a form of accommodation:

> *"There is no fairness to everyone, because everyone is unique and different. If anything, AI is accommodating its customers and giving them its calculated best options. This is optimization. I don't see the unfairness to customers, this only hurts small businesses who are trying to get exposure." (US1)*

This account suggests that for some consumers, algorithmic differentiation is not perceived as bias but as a rational market mechanism, a perspective that contrasts sharply with participants who considered such practices to be discriminatory. These varying interpretations suggest that how consumers evaluate algorithmic differentiation depends not only on their experiences, but also on how they conceptualize fairness itself.

When presented with a hypothetical scenario in which a platform systematically charged higher prices to people from certain countries, responses ranged across a spectrum. US3 expressed absolute rejection:

> *“If I found out that some group was being charged more because they use it more, then I'm not going to support that business practice. That's discrimination.” (US3)*

CA1 similarly stated he “would not shop there again”, and FI1 described it as “non-ethical, money hungry style”. VN2 said she would leave the platform unless it offered exclusive products unavailable elsewhere.

Participants appeared to draw a consistent line between acceptable and unacceptable platform behavior. Within-platform personalization - seeing recommendations based on browsing history on the same website - was generally accepted as a reasonable and expected feature. Nonetheless, cross-platform data movement was perceived differently. FI1 described personalization on a single website as “fine and understandable” but information moving between platforms as “creepy”. Conversational surveillance represented the hardest boundary: the experience of IND1 of receiving targeted ads after a private bedroom conversation and the case of US3 of spoken products appearing as advertisements illustrate the point at which AI-driven data practices were perceived as having crossed a fundamental line.

Regarding accountability for unfair or harmful AI outcomes, respondents reached near-universal agreement that the companies deploying AI systems bear primary responsibility. US3 drew an analogy to existing regulatory frameworks:

> *“That's why we depend on the government to set up guard rails and look out for us. When we buy some food or tool, we trust that it's been through the regulatory process. The same should happen with e-commerce.” (US3)*

VN1 proposed a model involving companies, government regulation, and independent third-party reviewers. IND1 suggested that while governments set the rules, companies must implement them in practice. FI1 noted that without clear regulation, “if something goes wrong, there's no one to hold accountable.”

Overall, these findings suggest that most participants did not fully trust AI-driven systems but continued to engage with them under conditions they actively defined, weighing perceived usefulness against fairness concerns and maintaining boundaries around practices that were deemed unacceptable.

Cross-cultural insights

Trust formation patterns appeared to differ across participants from various cultural backgrounds. Vietnamese participants typically adopted an outcome-based orientation, VN3 trusted businesses with good reputation, VN2 described AI as a “powerful supporter” while simultaneously expressing zero trust in the overall system, suggesting a possible distinction between trusting the function and distrusting the institution. Both FI1 and US3 seemed to demand process-based transparency, with FI1 actively choosing privacy-oriented alternatives recommended by IT communities. CA1’s trust, as discussed above, appeared grounded in institutional infrastructure rather than platform performance. As to perceived fairness, the responses of participants to differential pricing appeared to vary less by cultural background and more by technical knowledge. The cross-border participants appeared to develop comparative trust frameworks through their lived experience in multiple regulatory environments, suggesting that exposure to different digital ecosystems may allow consumers to calibrate their expectations more precisely.

Table 2. Summary of Thematic Findings

Theme	Core Insight	Illustrative Quotations	Implications
1.Experiencing AI-Driven Personalization and Inferred Data	Personalization was experienced as both beneficial and uncomfortable; accuracy made tracking visible and inferred data intensified discomfort	*"convenient for me, giving me more options"* (VN2); *"It's both intrusive and convenient"* (US3); *"tracking my browsing behavior quite closely"* (VN1); *"like a small assistant"* (VN2); *"no privacy even in bedroom"* (IND1); *"too many and too accurate… I feel a bit tired"* (VN2)	Convenience and discomfort coexisted rather than cancelling each other out; consumers managed this ambivalence instead of resolving it
2.Data Collection, Normalization, and the Limits of Acceptance	Data collection became a taken-for-granted aspect of digital life; concerns did not lead to behavioral change, yet participants refused when trade-offs were made explicit	*"part of the online shopping experience"* (US1); *"getting used to it"* (US4); *"we don't always notice"* (FI1); *"Boil the frog slowly"* (US3); *"convenience and price will 90% of the time outweigh any moral stance"* (US3); *"anything free only exists in a mousetrap"* (VN2); *"I can't say that I'm not gonna use those services again"* (NE1)	Gradual normalization led consumers to tolerate data collection by habit, but this habitual tolerance differs from genuine consent; how the trade-off is presented determines whether consumers accept or resist
3.Consumer Autonomy, Algorithmic Influence, and the Opacity of AI-Driven Systems	Participants expressed belief in their own independent decision-making while describing being subtly influenced; opacity of systems reinforced this tension	*"I tend to pay more attention to it"* (VN1); *"pushes to a certain direction"* (IND1); *"I can choose freely… but the AI things influence a lot"* (NE1); *"never feels pushed"* (US1); *"Very subtly… I do need this thing" (US4); "Terms and conditions are often vague on purpose"* (FI1); *"I might feel more worried than reassured"* (VN2)	Limited visibility into how platforms operate made it difficult for consumers to recognize or resist algorithmic influence; greater transparency risked increasing anxiety rather than empowerment
4.Conditional Trust, Perceived Fairness, and the Boundaries of Acceptance	Trust was conditional and maintained through self-verification rather than confidence in platforms; perceptions of algorithmic fairness varied widely, and participants drew firm boundaries around unacceptable practices	*"what matters more is whether the recommendations are useful"* (VN1); *"I wouldn't trust my handsaw to make a sandwich"* (US3); *"consumer protection laws are fairly robust"* (CA1); *"treated differently and not completely fairly"* (VN2); *"That's discrimination"* (US3); *"if something goes wrong, there's no one to hold accountable"* (FI1)	Continued platform use reflected pragmatic reliance rather than genuine trust; consumers compensated through self-verification, and drew firm boundaries where practices, such as cross-platform tracking or differential pricing, were perceived as unfair.

4.5 Summary of Findings

Across the four themes, the findings suggest that the responses of consumers towards AI-driven e-commerce reflect neither mere acceptance nor outright rejection. Even though AI-driven personalization was generally appreciated for its advantages, discomfort could emerge when it intensified into more advanced forms. The concerns were raised when consumers perceived that platforms used data that they had not intentionally shared.

Data collection practices were described as something that most participants had acknowledged, they gradually accepted as part of online shopping, sustained by convenience, and in some cases, a lack of alternatives. Nevertheless, when they were asked directly whether they would trade privacy for better deals, almost all the participants refused. This suggests that tolerating data practices in everyday use is not the same as agreeing to them.

There was a recurring tension between participants believing they choose freely and descriptions of being influenced by algorithmic systems in ways they did not always recognize. The opacity of platform practices reinforced this tension, the majority of the participants had never read a privacy policy, and some of them indicated that knowing more about data use could make them more uncomfortable rather than more confident. Trust in AI systems was generally low to moderate, maintained through personal verification rather than confidence in the platforms themselves. Participants drew clear lines around what they considered acceptable, with cross-platform tracking and conversational surveillance representing the strongest points of discomfort. Views on algorithmic fairness ranged widely, with some considering differential pricing as a normal business practice while others called it discrimination. Although these patterns were observed among participants from different cultural backgrounds, how they were expressed, the metaphors used, the degree of concern voiced, and the boundaries drawn, they are varied noticeably across the sample. Overall, the findings suggest that consumers do not simply accept AI-driven commerce. Rather, they perceive, evaluate, and conditionally engaged with these systems, expressing concerns, deploying countermeasures, and drawing boundaries around practices they consider unacceptable.

5 Discussion and Conclusion

5.1 Discussion

Across the findings, a recurring pattern can be observed: consumer responses to AI-driven e-commerce, such as hyper-personalization, inferred data practices, and algorithmic bias, are best understood not as acceptance or rejection but as a continuous process of conditional engagement. Consumers are constantly assessing, adjusting to and placing limits on these systems and the terms of this interaction are shaped by how useful consumers find these systems, how opaque the systems are, how dependent consumers are on digital platforms, and the cultural context in which they operate.

Trust as conditional and self-managed. The conditional nature of this engagement is most visible in how participants formed and maintained trust. The present findings are generally in line with the trust model created by McKnight et al. (2002) but indicate that in opaque algorithmic environments, trust is less of a state to be created and rather an ongoing practice. The most common method was trust-but-verify: VN3, VN1, and VN2 described cross-checking recommendations, comparison between different platforms, and seeing AI outputs as a reference only, not something to follow directly.

The data suggested three general trust orientations that should be interpreted as trends rather than fixed categories. The outcome-based trust was found in the participants who rated AI systems mainly based on their outcomes. VN1 emphasized that usefulness of recommendations mattered most to him, while CA1 treated AI as just one source of information among others; the process-based trust was found with the participants who needed a certain knowledge of how systems work as shown by US3's handsaw metaphor and FI1's focus on understanding what actually happens behind the system; the institution-based trust was revealed in the account of CA1 as the trust was was based on the regulatory environment, specifically his confidence that consumer protection laws in Canada are strong and properly enforced.

One such example was VN2, who explained AI system as a powerful supporter in her shopping but had zero trust in the system in general. This suggests that consumers can rely on AI functions because they perceive usefulness, at the same time, they can also distrust the platforms and institutions behind those functions. Underlying these conditional responses, several participants appeared to hold back trust not because the system had failed them, but because they could not see enough of how it worked to feel free when using it. VN2’s mousetrap metaphor and IND1’s unease about platforms knowing his gold purchases point to a similar logic: when consumers do not understand a system well enough, trusting it feels like an invitation for trouble that one cannot yet foresee. Cabiddu et al. (2022) suggest that trust may strengthen or weaken as users become more familiar with a system and observe its consistency, reliability, and alignment with their expectations. VN2’s experience illustrates one dimension of this dynamic that suggests trust in system practices and trust in who operates the system do not necessarily move in the same direction.

Additionally, the findings also indicate that the nature of trust that is formed by consumers can be shaped by the system opacity. Trust also seems to shift toward outcome-based assessment instead of informed assessment when system processes are ambiguous, that is, opacity does not merely decrease trust but may channel it towards specific orientations.

In terms of fairness, the data indicated the range of conceptualizations: VN3 perceived algorithmic differentiation as a common practice in the market, US1 redefined it as an optimization or accommodating, VN1 recognized that outcomes could be unequal even without intentional unfairness, and US3 referred to the practice of differential pricing as discrimination. This difference implies that the perception of fairness, as described by Shin (2020), is also based on the way in which consumers make sense of the system practices rather than on what the algorithm does.

The privacy paradox revisited. The process of navigation of privacy also demonstrates conditional engagement by consumers. The ongoing difference between the stated concerns and the ongoing use of the platforms by participants is typical of the privacy paradox (Norberg et al., 2007), but the current results indicate that the privacy paradox is shaped by framing, normalization, and structural limitations rather than reflecting a mere attitude-behaviour gap.

A striking contrast in the data indicated the framing-dependent nature of the paradox. Participants willingly tolerated data collection when it was performed in the background. However, once the trade-off was explicitly presented, almost everyone said no: VN2 cited a Vietnamese saying about mousetraps, US3 said that he would prefer paying more rather than giving his additional data to algorithmic systems or tech broker, and IND1 said that he might provide false data. This is consistent with Martin's (2020) argument that disclosure behavior should not be equated with relinquishing privacy expectations, and thus cannot reliably indicate consumers' actual privacy preferences. US1, however, offered a different type of rationalization as she dismissed the importance of her own data, reasoning that one person's information is too small as a drop in the ocean of data to matter among billions of users. This suggests that some consumers may resolve the privacy paradox not through the kind of cost-benefit reasoning described by the privacy calculus (Culnan & Armstrong, 1999; Phelps et al., 2000), but by redefining the stakes as negligible, rendering the calculation itself unnecessary.

Normalization mechanisms were also apparent. The process has been described by US3 through his boiling-frog metaphor and contextualized it as a larger cultural reversal, remembering that the early internet culture stressed caution over the modern culture where sharing with each other is normalized. NE1 compared it to sustainability behavior, noting that people often express concern but fail to change their habits in practice. Beyond normalization, consumers also continued using platforms because alternatives were limited as NE1 admitted that she was unable to quit using platforms because there were no real alternatives, this implies that continued engagement can reflect constraint as well as choice.

Inferred data reflected the point at which consumers can no longer weigh the costs and benefits of disclosing their data because the information is generated without their knowledge. When participants noticed that platforms were using information they had not intentionally provided, for example, when IND1 received targeted advertising in his device after a private conversation in his bedroom, or when US3 discovered that the products he only mentioned verbally were appearing as suggestions, their reaction shifts from calculated trade-offs to intense feelings of unease. These findings align with the analysis of Zhang et al. (2024) and Custers and Vrabec (2024), which suggested that users are often unaware of what information is being held about them and have limited control over data they do not intentionally provide. This is because inferred data exists within the ambiguity between observed events and algorithmic predictions. Such ambiguity may help explain why participants felt uncomfortable, as they could neither fully control nor clearly explain how those inferences were formed based on their data.

Consumer autonomy and algorithmic influence. Conditional engagement suggests that consumers think they are making active decisions. But one thing that kept coming up in the results was a contradiction between this belief and what participants described when talking about how algorithmic systems influenced them. In this work, building on the theoretical concerns raised by André et al. (2018) and Tiribelli (2024), the autonomy paradox refers to the gap between consumers saying they choose freely and their descriptions of being influenced by algorithmic systems in ways they did not fully recognize or control, a concept that runs parallel to the well-established privacy paradox. This pattern showed up across different participants and cultural groups, though it took different forms. VN1 said he chooses freely but then admitted he paid more attention to products marked as recommended. IND1 claimed that AI could not influence him much, then yet later became aware that AI pushed him to a certain direction. NE1 captured this tension most directly, as she described how what felt like free choice was in practice heavily shaped by algorithmic suggestions. US1 took a different approach, acknowledging that algorithms do limit what consumers see but reframing this as optimization rather than something restrictive. These findings align with André et al. (2018), suggesting that AI technologies can both support and constrain users, potentially reducing autonomy by subtly shaping consumer choices.

Tiribelli (2024) takes this a step further, arguing that algorithmic environments do not just shape individual choices but the broader contexts in which preferences and perceived needs take shape. There is some support for this in the data, though it should be read carefully given the self-reported nature of the interviews. US4, for instance, traced a path from seeing fitness content on social media to athletic wear ads to gradually feeling like she actually needed those products. US3 went further, suggesting that algorithmic systems help create entire cultural trends, communities, and followings around certain products. VN2 described something similar, saying recommendations created needs that were not there before. What these accounts suggest, taken together, is that algorithmic influence may not stop at directing attention or narrowing choices but could reach into how consumers come to define what they want in the first place.

Some participants described strategies for pushing back. VN2 talked about disciplining herself to buy what she needs rather than what she likes, CA1 said he always researches before visiting any platform, and VN3 anchored her decisions to a budget. But these strategies mostly seemed to work against the more visible forms of influence. The deeper process, where exposure to algorithmic content gradually shapes what feels like a genuine personal need, is harder to counter, especially when consumers cannot see how their choices are being structured behind the scenes.

Transparency, opacity, and informed consent. The findings suggest that both the autonomy paradox and the privacy paradox may stem from a shared underlying condition: the opacity of platform systems. Shin (2020) argues that when AI systems are perceived as fair, accountable, transparent, and explainable, users are more likely to trust them. What came through in this study, however, is that transparency does not always work that way, and in some cases it seemed to increase anxiety rather than build trust.

None of the participants reported having fully read the privacy policies of the platforms they use, which in itself says something about how these documents function in practice. FI1 went as far as suggesting that the vagueness of these documents is deliberate, not accidental. IND1 saw them differently, viewing privacy policies as a way for companies to protect themselves legally rather than to genuinely inform users. Whether seen as intentionally obscure or simply legalistic, the result is the same: the primary mechanism meant to keep users informed does not appear to be doing its job.

What was perhaps more surprising is that some participants indicated greater transparency could actually make them feel worse. VN2 explained that knowing more details about how platforms use data could make her more worried rather than more comfortable, because she would realize the extent of tracking might go beyond what she had assumed. This is worth pausing on, because it runs counter to the common assumption that more disclosure is always better. Karwatzki et al. (2017) had already found that transparency does not necessarily encourage consumers to share more data, but what VN2 describes goes further: it is not that detailed disclosure fails to help, but there is a possibility that it actively increases discomfort, presumably because the extent of tracking revealed exceeds what users had assumed was happening. In this study, we refer to this pattern as a transparency paradox, where greater disclosure leads to greater anxiety rather than increase trust.

Cultural dimensions as interpretive context. The patterns outlined above were observed across participants, although the ways in which consumers described them varied depending on their cultural contexts. Vietnamese participants, for example, tended to interpret personalization in relational terms. VN3 likened AI to a familiar seller, while VN2 described it as a small assistant supporting everyday household shopping. There is a sense of continuity here with existing consumer-seller relationships, where remembering what someone usually buys is simply part of good service, and AI-driven personalization may be received in much the same way, as something helpful rather than intrusive. US3, on the other hand, offered a more systemic critique and expressed a desire to detach from everything, which points to a quite different orientation, one that places greater weight on personal autonomy and the ability to opt out.

Trust also seemed to develop differently across participants. Some Vietnamese participants appeared to rely more on outcome-based trust, shaped by the kind of relational-commercial expectations described above, whereas FI1 and US3 placed stronger emphasis on understanding how systems actually operate, which is more in line with process-based transparency. Hallikainen and Laukkanen (2018) found that national culture influences trust in e-commerce, and the patterns observed here, while based on a small qualitative sample and not generalizable to national populations, do seem to point in a similar direction.

Revisiting the conceptual framework. The four-phase conceptual framework proposed in Chapter 2 is broadly supported by the findings, but the data suggests two refinements. First, the data from Phase 3 (Consumer Interpretations) showed two patterns that were not expected when the framework was designed: the difference between perceived and actual autonomy, where consumers perceived themselves as making free choices while at the same time describing how algorithms influenced what they saw and bought; and the result that higher levels of transparency might actually increase anxiety rather than trust, as VN2 said that she would be more anxious than reassured by detailed disclosure and IND1 expressed similar concerns about sensitive product purchases. According to Karwatzki et al. (2017), transparency does not always help to get consumers to share more data. The current results suggest that the effect can be more far-reaching: detailed disclosure concerning data practices not only failed to encourage sharing but seemed to have actually given rise to consumer anxiety. Second, the framework originally described Phase 4 (Consumer Responses) as outcomes, including the strengthening of trust, emotional reactions, or behavioral intentions. The results, however, suggest that these reactions are not stable states but ongoing and conditional: consumers might trust a platform when engaging in one kind of interaction but not another, or tolerate personalization to a certain extent but resist when it crosses a perceived boundary, with their reactions shifting depending on the situation.

Theoretical contributions. The findings offer several observations that may be relevant to existing theoretical discussions. The data suggest that trust in an opaque algorithmic environment is not merely present or absent, but is actively negotiated and managed by users through ongoing verification processes. Instead of being passively accepted, trust appears to depend on how users evaluate and interpret the output and the algorithmic system. In this process, three main orientations - outcome-based, process-based, and institution-based - emerge as key mechanisms shaping how trust is formed and maintained. There are two recurring patterns emerged from the data that were not anticipated by the conceptual framework: consumers consistently described themselves as choosing freely while also describing being influenced by algorithms, providing empirical grounding for concerns raised by André et al. (2018) and Tiribelli (2024), and some indicated that knowing more about data practices would make them more anxious rather than more confident, extending Karwatzki et al.'s (2017) findings on the limits of transparency. Finally, the way privacy trade-offs were presented appeared to affect how consumers responded, which is consistent with Martin's (2020) argument that disclosure behavior cannot reliably indicate consumers' actual privacy preferences, and cultural background appeared to influence how consumers interpreted these practices rather than whether they accepted them.

Broader reflections. These findings raise a broader consideration of the relation between consumers, AI-technology, and regulatory governance as the participants in this study have lived through the transition from the pre-internet world to AI-based commerce, and their skepticism may partly reflect their experience of witnessing technology change faster than their understanding of it. The lack of transparency they describe may also reflect deeper condition AI systems are often built by technology firms but used by e-commerce firms that had not developed them, so it is quite possible that the firms deploying these systems do not fully understand how AI-driven systems work or make inferences. This raise concerns as the system itself operates in a grey area. Regulatory frameworks tend to develop more slowly than the technologies they aim to govern, and consumers cannot always rely on legal protections to keep pace. Perhaps more concerning is what happens when this transition period is over as future generations grow up in the period where algorithmic influence is simply how things work, and the gradual normalization described by participants like US3 and NE1 may become so complete that there is no longer any basis for questioning it, though this concern goes beyond what the data can directly show. The findings suggest that the relationship between consumers, AI-driven systems, and the rules that govern them will need continued attention from all sides as the technology continues to evolve.

5.2 Implications

Although this study is exploratory and based on a small qualitative sample, the findings suggest several points that may be useful for practice and policy.

Personalization and data use. The results suggest that there is a comfort threshold in AI-based personalization, and once this comfort level is surpassed, hyper-personalization takes place. While hyper-personalization has positive effects in terms of reduced effort and increased relevance, it results in discomfort when accuracy leads to perceptions of surveillance and inaccuracy leads to constraints in the product space. Inferred data appeared to represent a particularly sensitive boundary, as qualitative differences in responses, moving from rational trade-offs to emotional discomfort, suggest that inferred data may need to be treated as a design constraint rather than merely a disclosure issue. Beyond design considerations, inferred data also raises ethical concerns. As US3 expressed the view that consumers should be able to browse and shop online without having a detailed profile built from their activity and then sold or shared without their knowledge or permission. This concern goes beyond algorithmic personalization as it involves the creation and commodification of consumer profiles based on data that consumers never intentionally provided. These observations suggest that firms may benefit from calibrating hyper-personalization intensity and providing users with meaningful mechanisms to correct, reset, or control their recommendation profiles.

Trust, fairness, and autonomy. The most consistent pattern in the data findings was a trust-but-verify approach as participants did not treat AI-based recommendations as something to follow directly, they see it as one input tool among others that they to check against their own judgment before making purchase decision. VN1, for instance, compared options across platforms before making a decision, and VN2 treated AI suggestions as reference only, not something to rely on completely. However, when it came to fairness, there were different perspectives as VN3 considered market segmentation to be a normal part of doing business while US3, by contrast, described differential pricing as discriminatory. This reflects that the same recommendation algorithm can be considered fair by one consumer and unfair or discriminatory by another as as each person has different expectations, particularly when such differences become visible between users. In addition, the findings also suggest that algorithmic influence can operate beyond product recommendations, potentially shaping what consumers come to perceive as needs. This points to a potential need for greater visibility into how recommendations are generated and meaningful options for users to adjust or limit the scope of algorithmic suggestions, so that consumers can make decisions they recognize as their own.

Consent, transparency, and accountability. The fact that there were no participants who read their respective privacy policy points to a potential weakness in current consent and notice-based models. The qualitative difference in responses to inferred data further supports the argument for consent and disclosure frameworks that differentiate between data provided intentionally by users and data inferred by platforms (Zhang et al., 2024; Custers & Vrabec, 2024). The transparency paradox adds another layer of complexity: the fact that participants would be more worried than reassured by full disclosure suggests that transparency should focus not only on how much information is provided but also on how it is presented and explained. The food safety analogy in US3 also suggests a potential regulatory gap in which, when firms deploy AI systems they did not develop, responsibility may become unclear and no party is ultimately accountable.

Cultural considerations. The variation in how participants from different cultural backgrounds interpreted AI-driven practices suggests that a one-size-fits-all approach to AI design and communication may not be equally effective across markets. Practices perceived as helpful service in one cultural context may be experienced as intrusive in another, suggesting that firms operating internationally may benefit from adapting their personalization strategies and transparency communications accordingly.

5.3 Limitations and Future Research

The qualitative sample of ten participants limits the generalization of the findings. However, it is consistent with the exploratory nature of the current research. Cultural observations, based on limited data from each group, should not be extrapolated to national levels. Different interview formats may result in differences in the depth and spontaneity of responses. Reliance on self-reported data means that the data only reflects the participant's perception of behavior. From the perspective of an interpretivist paradigm, these perceptions are the data of interest.

The current research's conceptual labels, such as the autonomy paradox and the transparency paradox, represent the researchers' interpretive framing of observed patterns. Although supported by the data, alternative readings are possible. Translation from participants native language to English may have introduced subtle shifts in meaning. The current data also represents a snapshot of the current state because of the rapidly changing technological and regulatory environment.

Further research could expand on whether these trends continue in larger and more diverse groups. Experimental studies could investigate the impact of specific AI practices on consumer behavior under controlled conditions. Longitudinal research could investigate how consumer responses develop over time. New research has begun to investigate the use of different types of AI, mechanical, thinking, and feeling, by digital service firms in international marketing strategies (Ojala et al., 2026). Future research could bridge the firm-side and consumer-side perspectives by examining the impact of specific AI deployment strategies on consumer experiences and the paradoxes identified in this study. Further research could investigate whether comparative evaluative frameworks develop systematically among participants with multi-country experience. Combining self-report data with behavioral measures could help test empirically the relationship between perceived autonomy and actual algorithmic influence.

5.4 Conclusion

Consumers neither accept AI-driven e-commerce passively, nor do they reject it outright. The current research suggests that consumer engagement is, in fact, conditional, negotiated, and shaped by forces that are only partially visible to them. Consumer engagement is conditional rather than a matter of simple acceptance or rejection. Personalization is accepted if it is considered to be useful, whereas rejection occurs when it crosses perceived boundaries. Trust, on the other hand, is maintained through active verification, not through passive acceptance. The terms of engagement, in turn, are shaped by perceived usefulness, system opacity, structural dependency, and cultural context.

The current research proposes two patterns that may extend the theoretical landscape. The autonomy paradox, defined as the gap between consumers' stated belief in their own free choice and their accounts of being influenced by algorithmic systems at the levels of attention, choice, and desire, offers a preliminary parallel to the privacy paradox. The transparency paradox, on the other hand, in which greater disclosure increases anxiety rather than building trust, complicates the assumption that transparency is a straightforwardly positive mechanism.

Trust is not an entity that is simply held but rather one that is actively managed. Three trust orientations were found: outcome-based, process-based, and institution-based, which represented different approaches to dealing with uncertainty in opaque algorithmic environments. The dominance of the trust-but-verify approach suggests that consumers view the information provided by AI as an input to their own decision-making rather than as authoritative recommendations.

Cultural context shapes interpretation, not determination. The background from which the participant hails was found to play an important role in the way in which the participant framed AI-driven practices, from the relational metaphors used by the Vietnamese to the systemic critique offered by the American, but functioned as an interpretive context rather than a deterministic variable. The experience of cross-border participants appeared to provide the basis for the development of comparative evaluative frameworks through exposure to different digital environments.

While these findings are based on a small exploratory sample and should be interpreted with caution, they point to a consistent pattern. In answering the central research question, the study found that consumers from different cultural backgrounds respond to AI-driven practices not through uniform acceptance or rejection but through individual patterns of interpretation, evaluation, and boundary-setting shaped by their personal experiences, social contexts, and cultural backgrounds. It is also worth noting that the participants in this study still carry a frame of reference from before AI-mediated commerce, which may be what allows them to notice and question these practices. As AI becomes further embedded in everyday digital life and regulatory frameworks continue to develop more slowly than the technologies they govern, the relationship between consumers, AI-driven systems, and the rules around them will require continued attention. Understanding the role of AI in e-commerce requires looking beyond what algorithms directly do, and also considering the subtle and often unseen ways they influence how consumers view their own choices, trust, and sense of autonomy, considerations that are relevant for researchers, platform designers, and policymakers who aim to develop AI systems that better reflect the diverse ways consumers experience and evaluate them.

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Appendices

Appendix 1. Interview Questions

Section 1. Background and Experience

1. Can you talk briefly about yourself and your online shopping habits? How often do you shop online, and which websites or apps do you use the most?
2. Can you tell me about a recent online shopping experience that you remember clearly, whether good or bad?

Section 2. Hyper-Personalization

3. When you browse a shopping platform, do you notice that the products or ads seem to be chosen specifically for you? How do you feel about that?
4. Has personalization ever felt helpful to you? Or have there been times when it felt uncomfortable, like you were being watched?
5. Do you think the system's suggestions help improve your shopping experience, or do they sometimes make you miss other options? Why do you think so?

Section 3. Inferred Data

6. Did you know that shopping platforms can record what you search for, which products you look at, and how long you spend looking, even if you don't buy anything?
7. How do you feel about shopping platforms using this kind of information to guess what you like or need?
8. If sharing more personal information meant you got better prices or more accurate suggestions, would you be willing to trade some of your privacy for that convenience? What do you weigh up when deciding?
9. Have you ever felt that a shopping platform knew too much about you - more than you were comfortable with? For example, you only mentioned a product to a friend, or just briefly looked at an item, but then ads for that exact product

kept showing up everywhere. If so, how did that make you feel, and did you do anything differently afterward?

10. Do you feel you can control what information shopping platforms collect about you? Why or why not?

Section 4. Algorithmic Bias and Fairness

11. Have you ever felt that a shopping platform treated you differently compared to others, for example, you saw different prices, different suggestions, or fewer options?
12. Do you think AI systems on shopping platforms treat everyone fairly, no matter where you come from or who you are?
13. Imagine you found out that a shopping platform consistently showed higher prices or fewer options to people from certain countries. Would that change how you feel about continuing to use it?

Section 5. Trust, Transparency, and Autonomy

14. Do you feel that shopping platforms clearly tell you how they use your data and why they suggest certain products to you?
15. Have you ever read the privacy policy or terms of use on a shopping platform? Were you able to understand what it said? fully or only partially?
16. If shopping platforms clearly explained why they suggest certain products to you, would you feel more comfortable using them? Why?
17. Do you think AI systems are influencing your shopping choices in ways you don't always notice? Can you give an example?
18. When you shop online, do you feel you're choosing freely, or do you sometimes feel the platform is pushing you in a certain direction?
19. Many people say they care a lot about privacy, but in practice, they still keep using platforms that collect a lot of data. Do you find this true for yourself? How do you explain that?

20. Do you think e-commerce companies should be responsible when their AI systems cause unfair or harmful results? In your view, who should be accountable -the company, the government, or someone else?
21. Overall, how much do you trust the AI systems on the platforms you use? What makes you trust or not trust them?

Section 6. Cultural Aspects

22. In your community or where you live, how do people generally feel about sharing personal information when shopping online? Is it seen as something normal, or do people tend to feel cautious or concerned?
23. In your life and social environment (family, friends, workplace), have people ever talked about being careful when using the Internet or sharing personal information? Has that influenced how you use shopping platforms today?
24. Have you ever shopped online while in a different country, or used a platform from another country and noticed the experience felt different compared to your home country? In what way?
25. Among your friends or community, how do people generally react when they find out shopping platforms track their behavior? Is this something people talk about, or is it rarely mentioned?
26. In your country or community, do people generally trust e-commerce platforms and their AI recommendation systems? Do they tend to accept them naturally, or are they more skeptical about how their data is used? Do you feel similar to people around you, or do you see things differently? Why?

Section 7. Closing

27. Looking back on everything we've talked about today, what is your biggest worry or biggest expectation about how AI is used in online shopping platforms?
28. Is there anything else about your experience with AI on shopping platforms that you'd like to share something we haven't covered yet?