International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 2, Mar-Apr-2026, ISSN (Online): 2395-566X

Impact of Personalization Algorithms on Consumer Decision Fatigue and Purchase Decision-Making in Digital Commerce Contexts

Nimisa Bhagchandani
CMS Business School
Bangalore, India

Abstract- — **The rapid growth of digital commerce and the increasing use of artificial intelligence have significantly changed the way consumers make purchase decisions online. One of the most common applications of AI in this space is the use of personalization algorithms, which provide users with tailored product recommendations based on their preferences and past behaviour. While these systems are designed to improve convenience and enhance user experience, they may also create unintended challenges for consumers. This study examines the impact of personalization algorithms on consumer decision fatigue and purchase decision-making in digital commerce contexts. The research focuses on understanding whether personalized recommendations simplify the decision-making process or contribute to cognitive overload. Decision fatigue is considered as a key factor that may influence how consumers respond to multiple product options and recommendations. The findings of the study are expected to provide insights into how personalization influences consumer behaviour beyond its intended benefits. It highlights the need for digital platforms to balance personalization with user comfort and cognitive ease. The study contributes to a better understanding of the psychological effects of personalization and its role in shaping online consumer decision-making.**

Keywords— Personalization algorithms, decision fatigue, purchase decision-making, digital commerce, consumer behaviour

I. INTRODUCTION AND REVIEW OF LITERATURE

1. Introduction

The use of Artificial Intelligence (AI) has increasingly become embedded in everyday life, often in ways that are not immediately visible to users. While the most obvious applications of AI involve tools used directly by individuals for tasks such as information retrieval, automation, and communication, many AI-driven processes operate in the background of digital platforms. One such application is the use of personalization algorithms. These algorithms analyse large volumes of data, including user interactions, purchase history, browsing behaviour, and demographic information, in order to generate personalized recommendations for individual users. By leveraging artificial intelligence and machine learning techniques, these systems are able to deliver customized product suggestions, content, experiences, and promotional messages that are tailored to the preferences of each consumer. In recent years, personalization algorithms have become a central feature of digital commerce environments. E-commerce platforms, streaming services, and social media networks rely heavily on algorithmic personalization to improve user engagement and increase conversion rates. Through features such as product recommendation engines, dynamic content feeds, and targeted promotions, companies are able to present consumers with offerings that are perceived as more relevant and appealing. From a marketing perspective, personalization allows firms to better understand consumer preferences and deliver messages that are aligned with individual needs and interests. As a result, personalization algorithms are often considered a powerful tool for enhancing customer experience and improving business performance.

Despite the advantages associated with algorithmic personalization, the growing reliance on these systems has also raised concerns about their unintended consequences. While personalized recommendations may increase convenience by narrowing down options for consumers, excessive personalization may also create a paradox in which consumers are exposed to an overwhelming number of highly tailored alternatives. When users are presented with numerous options that appear equally relevant, they may feel compelled to evaluate each alternative carefully in order to select the most suitable one. This process requires significant cognitive effort and can place considerable mental demands on the consumer.
One of the key psychological outcomes associated with such cognitive strain is decision fatigue. Decision fatigue refers to the mental exhaustion that occurs after individuals are required

to make repeated or complex decisions over a period of time. In digital commerce contexts, consumers frequently engage in activities such as comparing products, evaluating reviews, assessing prices, and considering multiple recommendation lists generated by personalization algorithms. Each of these interactions requires cognitive processing, and the cumulative effect of repeated decision-making can gradually deplete an individual's mental resources. As a result, consumers experiencing decision fatigue may find it more difficult to evaluate options effectively and may rely on cognitive shortcuts or emotional responses rather than careful reasoning.

Furthermore, the design of many digital commerce platforms encourages continuous engagement through persistent recommendations, targeted advertisements, and personalized promotions. While such strategies aim to capture consumer attention and stimulate purchasing behaviour, they may also contribute to information overload. When consumers are exposed to a large volume of personalized messages and product suggestions, the process of filtering and evaluating information becomes increasingly demanding. In some cases, consumers may respond to this overload by postponing decisions, abandoning purchase processes, or disengaging from the platform altogether.

Another important concern relates to the potential impact of personalization on consumer autonomy and exploration. By filtering content based on past behaviour and preferences, personalization algorithms may limit exposure to unfamiliar products or alternative options. While this filtering mechanism can increase relevance, it may also reduce opportunities for discovery and variety-seeking. Over time, consumers may perceive their choices as being shaped by algorithmic systems rather than their own preferences, which could influence their trust in digital platforms and their overall decision-making experience.

Given the widespread adoption of personalization technologies in digital commerce, it is important to examine not only their benefits but also their potential psychological effects on consumers. In particular, understanding how personalization algorithms influence decision fatigue and how this fatigue affects purchase decision-making can provide valuable insights for both researchers and practitioners. By exploring the relationship between algorithmic personalization, consumer decision fatigue, and purchasing behaviour, this study seeks to contribute to a deeper understanding of how digital commerce environments shape consumer decision processes. The present research therefore aims to examine the impact of personalization algorithms on consumer decision fatigue and purchase decision-making within digital commerce contexts.

2. Statement of the Research Problem

With the rapid growth of digital commerce, personalization algorithms have become a key part of how online platforms operate. E-commerce websites today rely heavily on data-driven systems to recommend products, display content, and offer promotions that match a user's preferences. These algorithms use past behaviour such as browsing history, previous purchases, and interactions to create a more customized experience. Because of this, personalization is often seen as a way to make shopping easier and more efficient for consumers.

However, this increasing dependence on personalization also raises an important concern. While these algorithms are meant to simplify decision-making, they may not always do so in practice. Instead of reducing choices, they often present consumers with multiple options that all appear relevant and appealing. This can make it harder for consumers to choose between alternatives, especially when the differences between products are not very clear. As a result, what is intended to be helpful may actually create confusion.

This situation can lead to decision fatigue. Decision fatigue refers to the mental exhaustion that occurs when a person has to make too many decisions or process too much information. In online shopping environments, consumers are constantly exposed to product recommendations, comparisons, reviews, and price variations. Each of these requires attention and evaluation. Over time, this can make the decision process tiring and overwhelming. Instead of carefully choosing the best option, consumers may start relying on shortcuts, delaying their decisions, or avoiding the purchase altogether.

Another issue is that digital platforms are designed to keep users engaged for longer periods of time. Continuous exposure to personalized suggestions, offers, and promotions increases the amount of information that consumers need to process. While this may increase engagement from a business perspective, it can also increase cognitive load for the consumer. In some cases, consumers may feel frustrated or mentally drained, which can negatively affect their overall shopping experience.

From an academic point of view, there is a gap in understanding this relationship. Most existing studies focus on the positive effects of personalization, such as improved customer satisfaction and higher purchase intention. On the other hand, research on decision fatigue mainly looks at situations involving too many choices or repeated decision-making in general contexts. There is limited research that directly examines whether personalization algorithms themselves contribute to decision fatigue, and how this fatigue affects purchase decision-making in digital commerce environments. This gap is important because it highlights a possible mismatch between what businesses intend to achieve and what consumers actually experience. If personalization leads to mental overload, it may reduce the effectiveness of the very strategy that is supposed to improve customer experience. Therefore, it becomes necessary to study this relationship more closely.

The present study aims to examine how personalization algorithms influence consumer decision fatigue and how this, in turn, affects purchase decision-making in digital commerce contexts. By doing so, the research seeks to provide a more balanced understanding of personalization and its impact on consumer behaviour.

2. Review of Literature

The growth of e-commerce and artificial intelligence (AI) has changed how consumers make decisions while shopping online. With the rise of digital platforms, consumers are now exposed to a large number of choices along with personalized recommendations. While this improves convenience and speed, it also creates challenges such as confusion, mental fatigue, privacy concerns, and reduced control over decisions.

One of the most important concepts discussed in the literature is choice overload, which occurs when consumers are faced with too many options. This makes it difficult for them to make decisions and often leads to frustration. According to Canarslan (2025), excessive choices increase decision fatigue, which is a state where individuals feel mentally exhausted after making repeated decisions. Using the Stimulus-Organism-Response (S-O-R) model, the study explains that choice overload acts as a stimulus, decision fatigue as the internal response, and behaviors like cart abandonment as the final outcome. This shows that too many options can actually reduce purchases instead of increasing them.

To solve this problem, many platforms use AI-based recommendation systems. These systems analyse user data such as past purchases, preferences, and browsing behavior to suggest relevant products. Research shows that these systems help reduce search effort and make decision-making easier (Hu, 2026). Similarly, recommendation agents simplify the shopping process by filtering options and presenting the most relevant ones, which improves user satisfaction and reduces confusion (Run, n.d.).

However, AI personalization has both advantages and disadvantages. On the positive side, it improves engagement and makes shopping more efficient. Studies show that personalized recommendations increase customer interest and satisfaction, leading to better decision-making (Journal of International Commercial Law and Technology, 2026). AI tools such as chatbots, dynamic ads, and voice assistants also influence different stages of the consumer journey and enhance the overall experience (Dek & Ibrahim, n.d.). In addition, AI can even be used to promote sustainable consumption by guiding users toward more environmentally friendly choices (Sathish et al., 2026).

On the negative side, personalization raises serious concerns about privacy and trust. Since AI systems rely heavily on user data, consumers often feel uncomfortable about how their information is collected and used. Research shows that while consumers enjoy personalized content, they are also worried about privacy risks and lack of transparency (Asghar, n.d.). This creates a situation where consumers continue to use these platforms despite concerns, which reflects the privacy paradox. Similarly, studies highlight that trust is essential for the success of AI systems, and companies must balance personalization with ethical data practices (Deepa et al., 2025).

Another important factor influencing online shopping behavior is the use of psychological triggers such as scarcity, urgency, and personalization. These techniques are widely used in marketing to push consumers toward making quicker decisions. According to Psychological Triggers in Online Shopping (n.d.), urgency and scarcity have a stronger impact on purchase intention compared to personalization alone. For example, messages like “only a few items left” or “limited-time offer” create pressure and increase the chances of purchase. However, excessive use of such tactics can make consumers feel manipulated and reduce trust.

As AI systems become more common, researchers have also identified the issue of algorithm fatigue. This happens when users feel tired or frustrated due to too many recommendations, especially when they are repetitive or irrelevant. According to Du et al. (n.d.), factors such as information overload, redundancy, and irrelevant content lead to emotional exhaustion and reduced engagement. Similarly, studies show that excessive personalization can lead to negative reactions such as algorithm aversion and discontinuance of use.

A related concept is the filter bubble, where users are only exposed to content that matches their previous behavior. While this increases relevance, it limits exposure to new options and reduces variety. Over time, this can lead to boredom and lower satisfaction (IGI Global, n.d.). Users may feel stuck seeing the same type of recommendations, which negatively impacts their overall experience.

AI also affects consumer autonomy, or the ability to make independent decisions. Recommendation systems often act as shortcuts, guiding users toward certain products. While this saves time, it can reduce independent thinking and create dependence on algorithms. According to Zhuang (n.d.), many consumers end up purchasing products they did not initially plan to buy due to algorithmic suggestions. Similarly, Dubazana and Nolwazi (2024) highlight that while AI improves efficiency, it can also reduce the sense of control and create discomfort among users.

These concerns have led to increased focus on ethical issues in AI. Researchers emphasize the need for transparent and responsible AI systems that respect consumer rights. Ethical personalization involves clearly informing users about data usage, providing control over preferences, and avoiding manipulative practices. Studies show that ethical AI and transparency can improve trust and long-term customer relationships (Trivedi, 2025). Additionally, responsible use of AI is becoming more important due to increasing regulations and consumer awareness.

Trust plays a key role in how consumers respond to AI-driven systems. When consumers trust a platform, they are more likely to engage with it and follow its recommendations. However, lack of transparency, excessive targeting, and perceived surveillance can lead to dissatisfaction and even brand abandonment (Understanding Customer Responses…, n.d.). Research also shows that many consumers do not fully understand how AI systems work, which increases confusion and uncertainty.

Another important aspect is that consumer behavior is not the same for everyone. Some consumers prefer to explore all options before making a decision, while others are satisfied with “good enough” choices. Recommendation systems may benefit some users more than others depending on their decision-making style (Run, n.d.). This shows that p ersonalization strategies need to be flexible and consider different types of consumers.

Overall, the literature shows that AI and personalization have both benefits and drawbacks. On one hand, they make online shopping faster, easier, and more convenient. On the other hand, they create challenges such as decision fatigue, privacy concerns, reduced autonomy, and algorithm fatigue. The key challenge for businesses is to balance efficiency with ethics and ensure that consumers feel comfortable and in control.

In conclusion, AI is playing a major role in shaping online consumer behavior. While it improves decision-making and enhances user experience, it also introduces new risks and challenges. Future research should focus on creating systems that support consumers rather than manipulate them. This includes improving transparency, protecting privacy, and designing user-friendly systems that build trust. As digital commerce continues to grow, understanding these factors will be essential for creating better and more sustainable online shopping experiences.

4. Identification of Research Gaps

The existing literature provides a broad understanding of how artificial intelligence and personalization algorithms influence online consumer behaviour. Several studies highlight the benefits of AI-driven recommendation systems in improving convenience, reducing search effort, and enhancing customer satisfaction. At the same time, research on concepts such as choice overload and decision fatigue explains how excessive options can negatively affect decision-making and lead to mental exhaustion.

However, most of these studies examine these concepts in isolation. Research on personalization algorithms mainly focuses on their positive outcomes, such as increased engagement and improved purchase intention. On the other hand, studies on decision fatigue largely focus on the effects of too many choices in general decision-making contexts rather than in algorithm-driven environments. There is limited research that directly connects these two areas.

Another important limitation is that many studies do not specifically examine how personalization itself may contribute to decision fatigue. While recommendation systems are often seen as tools that simplify decision-making, they may also increase cognitive load by presenting multiple relevant options. This creates a gap in understanding whether personalization reduces or increases decision fatigue in digital commerce settings.

Additionally, there is a lack of research that examines how decision fatigue influences purchase decision-making in the context of personalized recommendations. Although some studies discuss outcomes such as cart abandonment and reduced engagement, the direct relationship between decision fatigue and purchase behaviour in digital commerce environments is not sufficiently explored.

Therefore, there is a need for research that integrates these concepts and examines the relationship between personalization algorithms, decision fatigue, and purchase decision- making. This study aims to address this gap by analysing how perceived personalization influences decision fatigue and how this, in turn, affects consumer decision-making in digital commerce contexts.

5. Theoretical Underpinnings

This study is supported by key theories that explain how consumers process information and make decisions in digital environments. These theories help in understanding the relationship between personalization algorithms, decision fatigue, and purchase decision-making.

One of the main theories used in this study is Cognitive Load Theory. This theory suggests that individuals have a limited capacity to process information at a given time. When consumers are exposed to too much information, it becomes difficult for them to process and evaluate all available options. In digital commerce platforms, personalization algorithms often present multiple relevant product recommendations. While this is intended to simplify decision-making, it can also increase the amount of information that consumers need to process. As a result, consumers may feel overwhelmed, which can lead to decision fatigue. This theory helps explain how excessive personalized content can increase cognitive load and affect decision-making.

Another important theory is Ego Depletion Theory, which focuses on mental energy and self- control. According to this theory, making repeated decisions over time reduces an individual's cognitive resources. As consumers browse through online platforms, they are required to continuously evaluate products, compare alternatives, and make choices. This repeated decision-making process can lead to mental exhaustion, also known as decision fatigue. When consumers experience this state, they may rely on shortcuts, delay decisions, or avoid making a purchase altogether.

Together, these theories provide a strong foundation for the study. Cognitive Load Theory explains how too much information affects the consumer, while Ego Depletion Theory explains how repeated decision-making leads to mental exhaustion. Both theories support the idea that personalization algorithms, although useful, may also contribute to decision fatigue and influence purchase decision-making in digital commerce contexts.

II. RESEARCH METHODOLOGY

1. Scope of the Study

This study focuses on understanding the impact of personalization algorithms on consumer decision fatigue and purchase decision-making within digital commerce environments. The scope of the research is limited to online shopping platforms such as e-commerce websites and mobile applications where algorithm-driven recommendations are commonly used. These platforms rely heavily on user data to display personalized products, offers, and content, making them an appropriate setting for examining the effects of personalization on consumer behaviour.

The study specifically examines three key concepts: personalization algorithms, decision fatigue, and purchase decision-making. Personalization algorithms are considered from the perspective of consumer perception, meaning how users experience and interpret the recommendations shown to them. The study does not attempt to analyse the technical functioning of algorithms, but rather focuses on how these systems influence consumers psychologically. Decision fatigue is studied as a cognitive outcome that arises when consumers are exposed to repeated or complex choices. Purchase decision-making is examined in terms of how easily and confidently consumers are able to make buying decisions in digital environments.

The population for this study consists of individuals who actively use digital commerce platforms for shopping. The research primarily targets consumers who are familiar with online shopping and have experience interacting with personalized recommendations. Since the study is based on self-reported data, it captures the perceptions and experiences of users rather than their actual behaviour on platforms. The findings are therefore limited to perceived effects rather than objective measures of algorithm performance.

In terms of methodology, the study is restricted to a quantitative research approach using a structured questionnaire. Data is collected through a survey, and the responses are analysed to identify relationships between the variables. The study does not include experimental or longitudinal methods, and it does not account for changes in behaviour over time.

Overall, the scope of this research is confined to examining the relationship between personalization, decision fatigue, and purchase decision-making in digital commerce contexts. It does not extend to other industries, offline retail environments, or technical aspects of artificial intelligence systems.

2. Research Objectives

The main objective of this study is to examine how personalization algorithms influence consumer decision fatigue and purchase decision-making in digital commerce environments. With the increasing use of algorithm-driven recommendations on online platforms, it becomes important to understand how these systems affect consumers not only in terms of convenience, but also in terms of their mental effort and decision processes.

The objectives of the study are as follows:

- To examine the relationship between personalization algorithms and decision fatigue among consumers in digital commerce platforms.
- To analyse the effect of decision fatigue on consumer purchase decision-making.
- To study the direct relationship between personalization algorithms and purchase decision- making.
- To understand whether decision fatigue acts as a mediating factor between personalization algorithms and purchase decision-making.
- To gain insights into consumer perceptions of personalized recommendations in digital commerce environments.

3. Framing of Research Hypotheses

Based on the research objectives and the conceptual framework of the study, the following hypotheses have been formulated to examine the relationship between personalization algorithms, decision fatigue, and purchase decision-making in digital commerce contexts. These hypotheses aim to test both the direct and indirect effects of personalization on consumer behaviour.

The hypotheses for the study are as follows:

- H1: There is a significant relationship between personalization algorithms and decision fatigue among consumers.
- H2: There is a significant relationship between decision fatigue and purchase decision- making among consumers.
- H3: There is a significant relationship between personalization algorithms and purchase decision-making among consumers.
- H4: Decision fatigue mediates the relationship between personalization algorithms and purchase decision-making.

These hypotheses are designed to capture the key relationships between the variables under study. The first hypothesis focuses on understanding whether personalization contributes to cognitive strain. The second hypothesis examines how this cognitive state affects consumer decision behaviour. The third hypothesis explores whether personalization has a direct influence on purchase decision-making. Finally, the fourth hypothesis tests the mediating role of decision fatigue in explaining the relationship between personalization and consumer purchase decisions.

4. Research Design

The research design of a study provides the overall framework for collecting and analysing data in a systematic manner. It helps in ensuring that the research objectives are addressed effectively and that the findings are reliable. The present study adopts a quantitative research approach to examine the relationship between personalization algorithms, decision fatigue, and purchase decision-making in digital commerce contexts.

A quantitative approach has been chosen because the study aims to measure consumer perceptions and analyse relationships between variables using numerical data. Since the research focuses on identifying patterns and testing hypotheses, a structured and measurable method is considered appropriate. This approach allows for statistical analysis and helps in drawing objective conclusions based on the collected data.

The study is descriptive and analytical in nature. It is descriptive because it seeks to understand consumer experiences with personalization algorithms and their impact on decision fatigue. At the same time, it is analytical as it examines the relationships between the variables and tests the proposed hypotheses. The research goes beyond simply describing behaviour and attempts to explain how and why these relationships exist.

Data for the study is collected through a structured questionnaire administered to respondents who actively use digital commerce platforms. The questionnaire includes a mix of Likert scale, frequency-based, and multiple-choice questions designed to capture consumer perceptions and experiences. This method is suitable as it allows for collecting data from a large number of respondents in a relatively short period of time. It also ensures consistency in responses, which is important for statistical analysis.

The study follows a cross-sectional research design, meaning that data is collected at a single point in time rather than over an extended period. This approach is appropriate given the time constraints of the study and the nature of the research objectives. It provides a snapshot of consumer behaviour and perceptions related to personalization and decision fatigue in digital commerce environments.

The use of a survey-based method also allows for analysing relationships between variables such as personalization, decision fatigue, and purchase decision-making. Statistical techniques can be applied to test the hypotheses and identify significant relationships. However, since the study relies on self-reported data, it reflects the perceptions of consumers rather than their actual behaviour.

Overall, the chosen research design is suitable for examining the impact of personalization algorithms on consumer decision fatigue and purchase decision-making. It provides a structured and efficient way to collect and analyse data, while remaining aligned with the objectives of the study.

5. Methods for Data Collection & Variables of the Study

The data for this study has been collected using a primary research method in the form of a structured questionnaire. Since the objective of the study is to understand consumer perceptions and experiences, a survey-based approach was considered most suitable. The questionnaire was designed to capture responses related to personalization algorithms, decision fatigue, and purchase decision-making in digital commerce environments. The survey was distributed online to respondents who actively use digital commerce platforms for shopping.

The questionnaire consists of a combination of different types of questions, including:

- Likert scale questions
- Frequency-based questions
- Multiple-choice questions

This mix of question types helps in capturing different aspects of consumer behaviour while keeping the survey simple and easy to complete. The use of a structured format ensures consistency in responses, making it easier to analyse the data using statistical methods. The questionnaire is divided into different sections, each corresponding to a specific variable in the study, along with a section for demographic information.

The first section of the questionnaire collects demographic details such as age, gender, frequency of online shopping, preferred platform, and time spent browsing. This information helps in understanding the profile of the respondents and allows for basic segmentation during analysis. While demographic variables are not the main focus of the study, they provide useful context for interpreting the results.

The main variables of the study are outlined below:

Independent Variable (IV): Perceived Personalization Algorithms

This variable refers to the extent to which consumers perceive that digital commerce platforms provide personalized recommendations based on their preferences, browsing history, and past purchases. It captures how relevant and tailored the recommendations appear to the user.

Mediating Variable (MV): Decision Fatigue

This variable represents the mental exhaustion experienced by consumers as a result of repeated decision-making and exposure to multiple product options. It reflects the cognitive load faced by users while interacting with digital commerce platforms.

Dependent Variable (DV): Purchase Decision-Making

This variable refers to how consumers make purchasing decisions in digital commerce environments. It includes aspects such as decision difficulty, delay in making purchases, and the likelihood of abandoning a purchase due to cognitive overload. Each of these variables is measured using multiple items in the questionnaire to ensure reliability and consistency.

Personalization algorithms are measured from the perspective of consumer perception. Since it is not possible to directly measure the technical functioning of algorithms through a survey, the study focuses on how users experience personalization on digital platforms. This includes whether product recommendations match their interests, whether the platform appears to understand their preferences, and how frequently they encounter tailored suggestions.

Decision fatigue is measured as a psychological outcome resulting from exposure to multiple choices and repeated decision-making. The questionnaire includes items that assess whether consumers feel overwhelmed by the number of options available, whether they experience mental tiredness while comparing products, and whether the decision-making process becomes exhausting over time.

Purchase decision-making is measured in terms of how consumers respond to the decision process in digital commerce environments. Instead of focusing only on purchase intention, the study also considers behaviours such as delaying a purchase, leaving the platform without buying, and difficulty in making decisions. This provides a more realistic understanding of how decision fatigue affects consumer behaviour.

All scale-based items in the questionnaire are measured using a five-point Likert scale ranging from strongly disagree to strongly agree, along with equivalent frequency and intensity scales where applicable. Using multiple items for each variable helps improve the reliability of the measurements and allows for more accurate analysis.

Overall, the data collection method and variable measurement approach are aligned with the objectives of the study. The use of a structured questionnaire enables efficient data collection, while the selected variables provide a clear framework for analysing the relationship between personalization algorithms, decision fatigue, and purchase decision-making in digital commerce contexts.

III. DATA ANALYSIS AND INTERPRETATION

1. Techniques for Data Analysis

The data collected for this study is analysed using statistical techniques in order to examine the relationships between personalization algorithms, decision fatigue, and purchase decision- making. Since the study follows a quantitative approach, the analysis is based on numerical data collected through a structured questionnaire. The data is processed and analysed using statistical software such as SPSS, which allows for efficient handling of large datasets and application of various statistical tools.

The first step in the analysis involves data preparation and descriptive statistics. Before analysis, the collected data is cleaned by removing incomplete or inconsistent responses and coding the responses into numerical values. Descriptive statistics are then used to analyse demographic data such as age, gender, frequency of online shopping, and time spent browsing. Measures such as mean, frequency, and percentage are used to provide a clear overview of the sample and understand respondent characteristics.

The next step involves testing the reliability of the measurement scales used in the questionnaire. Reliability is assessed using Cronbach's Alpha, which measures the internal consistency of the items used to represent each variable. This ensures that the questions used for each construct are measuring the same underlying concept. A Cronbach's Alpha value above 0.7 is generally considered acceptable, indicating that the scale is reliable for further analysis.

Correlation analysis is then conducted to examine the relationships between the main variables of the study. This helps in identifying whether there is a positive or negative relationship between personalization algorithms, decision fatigue, and purchase decision-making. The strength and direction of the relationship are determined using correlation coefficients, while statistical significance is evaluated using p-values.

Further, regression analysis is used to test the hypotheses of the study. Regression helps in understanding the extent to which one variable influences another. Separate regression analyses are conducted to examine the effect of personalization algorithms on decision fatigue, the effect of decision fatigue on purchase decision-making, and the direct relationship between personalization and purchase decision-making. This method allows for identifying the predictive power of each variable and the overall model.

In addition to this, mediation analysis is conducted to examine whether decision fatigue acts as a mediating variable between personalization algorithms and purchase decision-making. This helps in understanding whether the effect of personalization on consumer decisions occurs directly or indirectly through decision fatigue. The analysis considers both direct and indirect relationships between the variables.

Overall, these statistical techniques provide a structured and systematic approach to analysing the data. They help in ensuring that the findings are reliable, valid, and aligned with the objectives of the study, while also allowing for clear interpretation of the relationships between the key variables.

2. Hypotheses Testing and Methods

The hypotheses formulated for this study are tested using statistical methods to examine the relationships between personalization algorithms, decision fatigue, and purchase decision- making. Since the study follows a quantitative approach, hypothesis testing is carried out using numerical data collected through a structured questionnaire. The analysis is conducted using statistical software such as SPSS, which allows for systematic testing of relationships between variables.

The first hypothesis (H1) states that there is a significant relationship between personalization algorithms and decision fatigue. This relationship is tested using regression analysis, where personalization algorithms are treated as the independent variable and decision fatigue as the dependent variable. The purpose of this analysis is to determine whether exposure to personalized recommendations increases cognitive load and contributes to decision fatigue. The significance of this relationship is evaluated using the p-value, while the strength and direction are assessed using the regression coefficient.

The second hypothesis (H2) examines the relationship between decision fatigue and purchase decision-making. This is also tested using regression analysis, with decision fatigue as the independent variable and purchase decision-making as the dependent variable. This test helps in understanding whether higher levels of mental exhaustion affect consumers' ability to make purchase decisions, leading to behaviours such as delay or avoidance.

The third hypothesis (H3) tests the direct relationship between personalization algorithms and purchase decision-making. This is analysed using regression to determine whether personalization has a direct influence on consumer decision behaviour. This step is important to understand whether personalization affects purchase decisions independently, without the influence of decision fatigue.

The fourth hypothesis (H4) examines whether decision fatigue mediates the relationship between personalization algorithms and purchase decision-making. Mediation analysis is used to test whether the effect of personalization on purchase decisions occurs indirectly through decision fatigue. This involves comparing the direct effect of personalization on purchase decision-making with the indirect effect through the mediating variable. If the inclusion of decision fatigue reduces the strength of the direct relationship, it indicates the presence of mediation.

In addition to regression analysis, correlation analysis is used to support the findings by identifying the strength and direction of relationships between variables. The acceptance or rejection of each hypothesis is based on the level of statistical significance, with a p-value of less than 0.05 considered significant. This ensures that the conclusions drawn from the analysis are based on reliable and statistically valid results.

Overall, these methods provide a structured approach to testing the hypotheses and help in clearly understanding the relationships between personalization algorithms, decision fatigue, and purchase decision-making.

3. Data Analysis & Interpretation Reliability Analysis

In order to ensure that the data collected through the questionnaire is consistent and dependable, a reliability analysis was conducted using Cronbach's Alpha. Reliability, in the context of research, refers to the extent to which a set of items consistently measures a particular construct. Since this study involves measuring abstract concepts such as personalization perception, decision fatigue, and purchase decision-making, it becomes important to verify that the items used under each variable are internally consistent.

Cronbach's Alpha is one of the most widely used measures of internal consistency. It evaluates how closely related a set of items are as a group. A higher value of Cronbach's Alpha indicates greater reliability of the scale. In general, a value above 0.7 is considered good, while values above 0.6 are considered acceptable, especially in exploratory research or studies involving behavioural constructs.

For this study, reliability analysis was conducted separately for each of the three main variables: personalization algorithms (independent variable), decision fatigue (mediating variable), and purchase decision-making (dependent variable). The results are discussed below. Reliability Analysis for Personalization Algorithms (Independent Variable)

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	112	100.0
	Excluded[a]	0	.0
	Total	112	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.639	5

Fig 1 Reliability statistics for personalization algorithms with Cronbach's Alpha value of 0.639

The construct of perceived personalization algorithms was measured using five items. These items were designed to capture how respondents perceive the relevance, accuracy, and usefulness of product recommendations provided by online shopping platforms. Since personalization is based on user experience and perception, it is expected that responses may vary slightly across individuals.

The Cronbach's Alpha value obtained for this construct is 0.639. This indicates an acceptable level of internal consistency among the items. While the value does not fall within the high reliability range, it is still considered suitable for further analysis, particularly in studies dealing with subjective perceptions and behavioural responses.

The moderate value of Cronbach's Alpha suggests that while the items are related, they are not perfectly aligned. This can be explained by the nature of personalization itself. Different respondents may interpret personalization differently based on factors such as their familiarity with technology, frequency of online shopping, and expectations from digital platforms. For some users, personalization may feel accurate and helpful, while for others it may appear repetitive or irrelevant. This variation in perception can lead to slight inconsistencies in responses across items.

Another possible reason for the moderate reliability is that the construct of personalization includes multiple dimensions, such as relevance, discovery, and perceived understanding by the platform. Since these aspects are not identical, some variation in responses is expected. However, this does not weaken the construct significantly; rather, it reflects the complexity of the concept being measured.

Despite the moderate Cronbach's Alpha value, the scale is considered reliable enough for the purpose of this study. There is no strong evidence to suggest that any individual item is significantly reducing the overall reliability. Therefore, all five items were retained and used in further statistical analysis. Reliability Analysis for Decision Fatigue (Mediating Variable)

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	112	100.0
	Excluded[a]	0	.0
	Total	112	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.880	4

Fig 2 Reliability statistics for decision fatigue with Cronbach's Alpha value of 0.880

The construct of decision fatigue was measured using four items that capture the mental exhaustion experienced by consumers when they are exposed to multiple choices and repeated decision-making. Unlike personalization, decision fatigue is a more direct psychological experience, which may lead to more consistent responses across individuals.

The Cronbach's Alpha value obtained for this construct is 0.880, indicating a high level of internal consistency. This suggests that the items used to measure decision fatigue are strongly correlated with each other and are effectively capturing the same underlying concept.

The high reliability value indicates that respondents have interpreted the items in a similar manner and have responded consistently across all four statements. This reflects that the construct of decision fatigue is clearly understood and experienced in a relatively uniform way by consumers. When individuals feel overwhelmed or mentally tired while shopping online, this feeling is consistently reflected across different aspects measured in the questionnaire.

The strength of the reliability score also indicates that the scale is stable and well-constructed. The items complement each other and do not introduce unnecessary variation. This is important because a reliable mediator strengthens the overall model and improves the accuracy of further analysis, especially when examining indirect relationships.

Given the strong Cronbach's Alpha value, all four items were retained without any modification. The decision fatigue construct demonstrates a high degree of reliability and can be confidently used for correlation, regression, and mediation analysis.

Reliability Analysis for Purchase Decision-Making (Dependent Variable)

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	112	100.0
	Excluded[a]	0	.0
	Total	112	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.772	3

Fig 3 Reliability statistics for purchase decision-making with Cronbach's Alpha value of 0.772

The construct of purchase decision-making was measured using three items. These items focus on consumer behaviour in terms of difficulty in making decisions, delay in purchasing, and reduced willingness to complete a purchase. Even though the number of items is relatively small, they are designed to capture key behavioural outcomes associated with decision fatigue.

The Cronbach's Alpha value obtained for this construct is 0.772, which indicates a good level of internal consistency. This suggests that the items are sufficiently correlated and are measuring related aspects of purchase decision-making.

The reliability value shows that respondents who experience difficulty or hesitation in making purchase decisions tend to respond similarly across all items. This indicates that the construct is being captured in a consistent manner. Despite having fewer items, the scale maintains a strong level of reliability, which reflects the clarity and relevance of the questions used.

It is also important to note that Cronbach's Alpha values can sometimes be influenced by the number of items in a scale. Since this construct includes only three items, achieving a value above 0.7 is considered a strong result. This further supports the reliability of the measurement.

Based on the results, all three items were retained for further analysis. The purchase decision- making scale is considered reliable and suitable for testing the proposed relationships in the study.

Overall Interpretation of Reliability Analysis
Overall, the reliability analysis indicates that all three constructs used in the study demonstrate acceptable to high levels of internal consistency. The independent variable shows acceptable reliability, while both the mediating and dependent variables demonstrate strong reliability. These results confirm that the measurement scales are suitable for further statistical analysis.

The findings also suggest that while some variation exists in the perception of personalization, the constructs of decision fatigue and purchase decision-making are measured more consistently across respondents. This provides confidence in the quality of the data and supports the validity of the subsequent analysis.
Descriptive Statistics Analysis

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
IV	112	2.67	5.00	3.6994	.49210
MV	112	1.00	5.00	3.1094	1.06795
DV	112	1.67	5.00	3.4762	1.01017
Valid N (listwise)	112				

Fig 4 Descriptive statistics including mean, minimum, maximum, and standard deviation

Descriptive statistics were used to summarize and understand the overall characteristics of the data collected for the study. This form of analysis provides a basic overview of the dataset by presenting measures such as mean, minimum, maximum, and standard deviation. It helps in identifying general patterns in the responses and gives an initial understanding of how respondents perceive the constructs under study.

In this research, descriptive statistics were calculated for the three main variables, namely personalization algorithms (independent variable), decision fatigue (mediating variable), and purchase decision-making (dependent variable). A total of 112 valid responses were included in the analysis, with no missing data, ensuring consistency and completeness of the dataset.

Descriptive Analysis for Personalization Algorithms (Independent Variable)
The descriptive statistics for the independent variable, perceived personalization algorithms, show a mean value of 3.6994, with a minimum value of 2.67 and a maximum value of 5.00. The standard deviation for this variable is 0.49210.

The mean value being closer to 4 indicates that, on average, respondents tend to agree that online shopping platforms provide personalized recommendations that match their preferences. This suggests that most users perceive personalization features to be moderately to highly effective. The relatively high mean reflects a generally positive perception of algorithm-driven recommendations among consumers.

The minimum value of 2.67 indicates that even the lowest average response is not extremely low, suggesting that very few respondents strongly disagreed with the personalization-related statements. On the other hand, the maximum value of 5.00 shows that some respondents strongly agree with the effectiveness of personalization, indicating a high level of satisfaction for certain users.

The standard deviation is relatively low, which indicates that the responses are not widely spread out from the mean. In simpler terms, most respondents have similar opinions regarding personalization, and there is limited variation in their responses. This consistency supports the earlier reliability findings and suggests that respondents have a fairly uniform perception of personalization algorithms.

Descriptive Analysis for Decision Fatigue (Mediating Variable)
The descriptive statistics for decision fatigue show a mean value of 3.1094, with a minimum value of 1.00 and a maximum value of 5.00. The standard deviation for this variable is 1.06795.

The mean value, being slightly above 3, indicates a moderate level of decision fatigue among respondents. This suggests that while consumers do experience mental exhaustion when making decisions online, the intensity of this experience is not extremely high across all respondents. It reflects a balanced situation where some users feel overwhelmed, while others manage the decision-making process more comfortably.

The minimum value of 1.00 indicates that some respondents reported no experience of decision fatigue, suggesting that not all consumers are affected by the abundance of choices. In contrast, the maximum value of 5.00 shows that some respondents experience a very high level of fatigue, highlighting the presence of strong individual differences in how consumers respond to digital shopping environments.
The standard deviation for this variable is relatively high compared to the independent variable. This indicates greater variability in responses, meaning that respondents differ significantly in their experience of decision fatigue. This variation can be explained by differences in individual tolerance levels, shopping habits, and decision-making styles. Some consumers may enjoy exploring multiple options, while others may feel overwhelmed quickly.

Descriptive Analysis for Purchase Decision-Making (Dependent Variable)
The descriptive statistics for purchase decision-making show a mean value of 3.4762, with a minimum value of 1.67 and a maximum value of 5.00. The standard deviation for this variable is 1.01017.

The mean value suggests that respondents moderately agree that their purchase decisions are affected by factors such as difficulty in choosing, delay in decision-making, or mental exhaustion. This indicates that purchase decision-making is influenced to a noticeable extent by the online shopping experience, though not uniformly across all individuals.

The minimum value of 1.67 indicates that some respondents do not face significant difficulty in making purchase decisions, suggesting that not all consumers are equally impacted. On the other hand, the maximum value of 5.00 reflects that some respondents strongly experience challenges in decision-making, including hesitation or avoidance of purchases.

The standard deviation is relatively high, indicating a considerable spread in responses. This suggests that consumers vary in how they approach purchase decisions. While some are decisive and quick in making purchases, others may struggle due to the overwhelming number of choices or mental fatigue.
Overall Interpretation of Descriptive Statistics

Overall, the descriptive statistics provide a clear picture of the data. The results indicate that consumers generally perceive personalization algorithms positively, as reflected by the relatively high mean value of the independent variable. At the same time, decision fatigue is experienced at a moderate level, with noticeable variation across respondents.

Purchase decision-making also shows moderate influence, suggesting that while some consumers are affected by cognitive overload, others are able to navigate the decision process more efficiently. The variation observed in the mediating and dependent variables highlights the role of individual differences in consumer behaviour.

Correlation Analysis

Correlations

		IV	MV	DV
IV	Pearson Correlation	1	.176	.091
	Sig. (2-tailed)		.063	.339
	N	112	112	112
MV	Pearson Correlation	.176	1	.527**
	Sig. (2-tailed)	.063		.000
	N	112	112	112
DV	Pearson Correlation	.091	.527**	1
	Sig. (2-tailed)	.339	.000	
	N	112	112	112

**. Correlation is significant at the 0.01 level (2-tailed).

Fig 5 Correlation matrix displaying Pearson correlation coefficients and significance values

Correlation analysis was conducted to examine the strength and direction of the relationship between the key variables of the study, namely personalization algorithms (independent variable), decision fatigue (mediating variable), and purchase decision-making (dependent variable). Pearson's correlation coefficient was used for this purpose, as it is suitable for measuring linear relationships between continuous variables.
The correlation coefficient (r) ranges from -1 to +1, where values closer to +1 indicate a strong positive relationship, values closer to -1 indicate a strong negative relationship, and values near 0 indicate little to no relationship. In addition to this, the significance value (p-value) is used to determine whether the observed relationship is statistically significant. A p-value less than 0.05 is generally considered significant.
Relationship between Personalization Algorithms and Decision

Fatigue

The correlation between personalization algorithms and decision fatigue was found to be r = 0.176, with a significance value of p = 0.063.

This indicates a weak positive relationship between the two variables. In simple terms, as the level of perceived personalization increases, decision fatigue also tends to increase slightly. However, the strength of this relationship is low, suggesting that personalization does not strongly influence decision fatigue in a consistent manner across all respondents. More importantly, the p-value is greater than 0.05, which means that the relationship is not statistically significant. This suggests that there is insufficient evidence to conclude that personalization algorithms have a meaningful impact on decision fatigue within the sample studied.

This finding is interesting because, theoretically, personalization is expected to either reduce decision fatigue by simplifying choices or increase it by presenting too many relevant options. However, the weak and insignificant relationship observed here indicates that personalization alone may not be a strong driver of decision fatigue. Other factors, such as individual differences, platform design, or type of product, may also play a role.

Relationship between Personalization Algorithms and Purchase Decision-Making

The correlation between personalization algorithms and purchase decision-making was found to be r = 0.091, with a significance value of p = 0.339.

This indicates a very weak positive relationship between the two variables. The value is close to zero, suggesting that there is almost no linear relationship between perceived personalization and how consumers make purchase decisions. The p-value is also significantly higher than 0.05, indicating that the relationship is not statistically significant. This means that personalization algorithms, in this study, do not appear to have a direct and measurable impact on purchase decision-making.

This result suggests that while consumers may notice and even appreciate personalized recommendations, these do not necessarily translate into actual decision outcomes such as making or delaying a purchase. It highlights that purchase decisions are influenced by multiple factors beyond personalization, such as price, trust, product need, and individual preferences.

Relationship between Decision Fatigue and Purchase Decision-Making

The correlation between decision fatigue and purchase decision-making was found to be r = 0.527, with a significance value of p = 0.000.

This indicates a moderate to strong positive relationship between the two variables. In practical terms, this means that as decision fatigue increases, it has a noticeable impact on purchase decision-making. Consumers who feel more mentally exhausted are more likely to experience difficulty in making decisions, delay their purchases, or avoid purchasing altogether.

The p-value is less than 0.01, which indicates that the relationship is highly statistically significant. This provides strong evidence that decision fatigue plays an important role in influencing consumer behaviour in digital commerce environments.

This finding aligns well with theoretical expectations. When consumers are exposed to too many options and required to process large amounts of information, their cognitive resources become depleted. As a result, their ability to make effective decisions decreases, leading to hesitation or avoidance behaviour.

Overall Interpretation of Correlation Analysis

Overall, the results of the correlation analysis reveal that decision fatigue is the most influential factor among the variables studied. While personalization algorithms show weak and statistically insignificant relationships with both decision fatigue and purchase decision-making, decision fatigue demonstrates a strong and significant relationship with purchase behaviour.

This suggests that the impact of personalization on consumer decision-making may not be direct. Instead, its influence may depend on how it affects the cognitive state of the consumer. However, in this study, personalization does not appear to significantly contribute to decision fatigue, which weakens the mediation pathway.

These findings provide important insights into consumer behaviour in digital commerce environments. They indicate that while personalization is a widely used strategy, its direct impact on decision-making may be limited. On the other hand, psychological factors such as decision fatigue play a more critical role in shaping consumer responses.

Regression Analysis and Interpretation

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	1.937	.637		3.039	.003		
	IV	-.003	.170	-.002	-.020	.984	.969	1.032
	MV	.499	.078	.528	6.385	.000	.969	1.032

a. Dependent Variable: DV

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Variance Proportions IV	Variance Proportions MV
1	1	2.922	1.000	.00	.00	.01
	2	.069	6.501	.04	.04	.99
	3	.009	18.378	.96	.96	.00

a. Dependent Variable: DV

Fig 6 Regression coefficients table showing effects of personalization and decision fatigue on purchase decision-making

Regression

```
[DataSet1] C:\Users\Manasi N J\Desktop\Nimisa analysis.sav
```

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	MV, IV[b]	.	Enter

a. Dependent Variable: DV

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.527[a]	.278	.265	.86604

a. Predictors: (Constant), MV, IV

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31.518	2	15.759	21.011	.000[b]
	Residual	81.752	109	.750		
	Total	113.270	111			

a. Dependent Variable: DV

b. Predictors: (Constant), MV, IV

Fig 7 ANOVA table and Model Summary showing R, R Square, Adjusted R Square, and standard error

To further examine the relationships between the variables and test the proposed hypotheses, multiple linear regression analysis was conducted. Regression analysis is a statistical technique used to understand the extent to which one or more independent variables influence a dependent variable. In the context of this study, the analysis was carried out to determine how personalization algorithms and decision fatigue impact purchase decision-making in digital commerce environments.
In this model, purchase decision-making was treated as the dependent variable, while personalization algorithms and decision fatigue were included as predictor variables. By including both variables in the same model, it becomes possible to assess not only their individual effects but also their combined explanatory power.

Model Summary and Overall Fit of the Model
The model summary provides an overview of how well the regression model fits the data. The R value of 0.527 indicates a moderate level of association between the independent variables and the dependent variable. This suggests that the predictors included in the model have a reasonable level of influence on purchase decision-making.

The R Square value of 0.278 indicates that approximately 27.8% of the variation in purchase decision-making can be explained by personalization algorithms and decision fatigue. While this may appear moderate, it is important to recognize that consumer behaviour is influenced by a wide range of factors, many of which are not captured in this model. These may include price sensitivity, brand loyalty, trust, urgency, and individual preferences. Therefore, an R Square value of this magnitude is considered acceptable in behavioural and social science research.

The Adjusted R Square value of 0.265 provides a more refined estimate by accounting for the number of predictors in the model. The relatively small difference between R Square and Adjusted R Square suggests that the model is stable and not overfitted. This indicates that the variables included in the model contribute meaningfully without introducing unnecessary complexity.

The standard error of the estimate is 0.86604, which reflects the average deviation between the observed and predicted values of the dependent variable. A moderate value suggests that while the model is reasonably accurate, there is still some level of unexplained variation, which is expected in studies involving human decision-making.

ANOVA and Significance of the Model
The ANOVA results are used to determine whether the overall regression model is statistically significant. The analysis shows an F-value of 21.011 with a significance level of $p = 0.000$.

Since the p-value is well below the threshold of 0.05, the regression model is considered statistically significant. This means that the predictors, when taken together, significantly explain variations in purchase decision-making. In other words, the model as a whole provides a better explanation of the dependent variable compared to a model with no predictors.

This result confirms that at least one of the independent variables included in the model has a meaningful impact on purchase decision-making.

Analysis of Regression Coefficients

The coefficients table provides detailed insights into the individual contribution of each predictor variable. It helps in understanding both the direction and strength of the relationship between each independent variable and the dependent variable.

Effect of Personalization Algorithms on Purchase Decision-Making

The unstandardized coefficient (B) for personalization algorithms is -0.003, with a significance value of $p = 0.984$. The standardized beta value is -0.002, which is extremely close to zero.

This indicates that personalization algorithms have no statistically significant impact on purchase decision-making. The relationship is not only insignificant but also practically negligible, as reflected by the near-zero beta value.

This finding suggests that while consumers may be exposed to personalized recommendations, these do not directly influence their final decision-making behaviour in a measurable way. It highlights a gap between perceived personalization and actual behavioural outcomes. Consumers may recognize personalization as a feature, but it does not necessarily translate into quicker or more confident purchase decisions.

Another possible interpretation is that personalization has become a standard feature across platforms, and therefore, consumers may no longer perceive it as a differentiating factor. As a result, its influence on decision-making may be limited or overshadowed by other factors such as product relevance, pricing, and urgency.

Effect of Decision Fatigue on Purchase Decision-Making

The unstandardized coefficient (B) for decision fatigue is 0.499, with a significance value of $p = 0.000$. The standardized beta value is 0.528, indicating a strong positive relationship.

This result shows that decision fatigue has a significant and substantial impact on purchase decision-making. As the level of decision fatigue increases, consumers are more likely to experience difficulty in making decisions, delay their purchases, or avoid making a purchase altogether.

The relatively high beta value indicates that decision fatigue is a dominant predictor in the model. Compared to personalization algorithms, its influence on purchase decision-making is much stronger and more consistent.

This finding aligns with theoretical expectations, particularly with concepts such as cognitive load and mental exhaustion. When consumers are required to process too many options or repeatedly evaluate alternatives, their cognitive resources become depleted. This reduces their ability to make effective decisions, leading to hesitation and avoidance behaviour.

Multicollinearity Diagnostics

To ensure the validity of the regression results, multicollinearity was assessed using tolerance and Variance Inflation Factor (VIF) values. Multicollinearity occurs when independent variables are highly correlated with each other, which can distort the results of regression analysis.

The tolerance values for both variables are 0.969, and the VIF values are 1.032, which are well within acceptable limits. Typically, VIF values below 5 indicate that multicollinearity is not a concern.

These results confirm that the predictor variables are independent of each other and do not overlap significantly in terms of the variance they explain. This strengthens the reliability of the regression model and ensures that each variable contributes uniquely to the analysis.

Overall Interpretation of Regression Results

The regression analysis provides a comprehensive understanding of how the variables interact with each other. While the overall model is statistically significant and explains a reasonable portion of variation in purchase decision-making, the individual effects of the variables differ considerably.

Decision fatigue emerges as the most influential factor, with a strong and statistically significant impact on purchase decision-making. This highlights the importance of psychological and cognitive factors in shaping consumer behaviour in digital environments.

On the other hand, personalization algorithms do not show a significant direct effect on purchase decision-making. This suggests that the role of personalization may be more complex than initially assumed. Rather than directly influencing decisions, its impact may depend on how consumers interpret and respond to personalized content.

Additionally, since personalization does not show a significant relationship with decision fatigue, the mediating effect is not supported in this study. This indicates that the expected pathway from personalization to decision fatigue and then to purchase decision-making is not strongly established in this dataset.

Overall, the findings suggest that while technological features such as personalization are widely implemented, their effectiveness in influencing actual consumer behaviour may be limited. In contrast, cognitive factors such as decision fatigue play a more critical role in determining how consumers make decisions.

IV. FINDINGS AND RECOMMENDATIONS

1. Research Outcome and Findings

The present study aimed to examine the impact of personalization algorithms on consumer decision fatigue and purchase decision-making in digital commerce environments. With the increasing use of artificial intelligence and data-driven recommendations, understanding how consumers respond to personalized content has become important. The study specifically focused on analysing whether personalization simplifies decision-making or contributes to cognitive overload, and how this influences purchase behaviour.

The findings of the study are based on data collected from 112 respondents who actively engage in online shopping. The analysis included reliability testing, descriptive statistics, correlation analysis, and regression analysis. These methods helped in examining both the strength and significance of relationships between the variables.

The descriptive statistics provided an initial understanding of the data. The mean score for personalization algorithms was relatively high, indicating that respondents generally perceive online platforms to offer moderately to highly personalized recommendations. This suggests that personalization is noticeable and relevant to users. At the same time, the mean score for decision fatigue was moderate, indicating that consumers do experience some level of mental exhaustion while making decisions online. The mean value for purchase decision-making also reflected moderate influence, suggesting that consumers sometimes face difficulty, delay, or hesitation while making purchase decisions.

The reliability analysis confirmed that the measurement scales used in the study were consistent and dependable. The independent variable, personalization algorithms, showed an acceptable level of reliability. While the value was not very high, it was sufficient for further analysis, especially considering the subjective nature of personalization. The mediating variable, decision fatigue, demonstrated a high level of reliability, indicating strong internal consistency among the items. The dependent variable, purchase decision-making, showed a good level of reliability despite having fewer items. Overall, the reliability results indicated that the data collected was suitable for further statistical analysis.

The correlation analysis provided insights into the relationships between the variables. The relationship between personalization algorithms and decision fatigue was found to be weak and statistically insignificant. This suggests that personalization does not strongly contribute to mental exhaustion among consumers. Although there was a slight positive relationship, it was not strong enough to establish a meaningful connection. This finding indicates that personalization, on its own, may not be a major factor in causing decision fatigue.

Similarly, the relationship between personalization algorithms and purchase decision-making was found to be very weak and statistically insignificant. This suggests that personalization does not have a direct influence on how consumers make purchase decisions. Even though consumers are exposed to personalized recommendations, these do not necessarily lead to quicker or more confident decision-making. This highlights that personalization may not directly translate into behavioural outcomes.

In contrast, the relationship between decision fatigue and purchase decision-making was found to be moderate to strong and statistically significant. This indicates that decision fatigue plays an important role in influencing consumer behaviour. As consumers experience higher levels of mental exhaustion, they are more likely to delay their decisions, feel uncertain, or avoid making a purchase. This finding highlights the importance of cognitive factors in shaping consumer decision-making in digital environments.

The regression analysis further strengthened these findings. The overall model was found to be statistically significant, indicating that the variables included in the study collectively explain variations in purchase decision-making. However, the individual effects of the variables showed clear differences.

Decision fatigue emerged as the most significant predictor of purchase decision-making. It had a strong positive relationship with the dependent variable, indicating that higher levels of fatigue lead to greater difficulty in decision-making. This confirms that cognitive overload negatively affects consumer behaviour and supports the theoretical understanding of decision fatigue.

On the other hand, personalization algorithms did not show a significant effect on purchase decision-making. The relationship was found to be negligible, indicating that personalization does not directly influence consumer decisions in a measurable way. This suggests that while personalization may enhance the browsing experience, it does not necessarily drive actual purchase behaviour.

The regression results also indicated that the mediating effect of decision fatigue was not supported. Since personalization did not have a significant relationship with decision fatigue, the indirect pathway was not established. This means that personalization does not significantly influence purchase decision-making through decision fatigue in this study.

Based on these findings, the hypotheses of the study can be evaluated. The first hypothesis, which proposed a relationship between personalization algorithms and decision fatigue, is not supported. The second hypothesis, which examined the relationship between decision fatigue and purchase decision-making, is supported. The third hypothesis, which proposed a direct relationship between personalization algorithms and purchase decision-making, is also not supported. Finally, the fourth hypothesis, which proposed a mediating effect of decision fatigue, is not supported.

Overall, the findings suggest that while personalization is a prominent feature of digital commerce platforms, its direct impact on consumer decision-making is limited. Instead, psychological factors such as decision fatigue play a more significant role in influencing how consumers behave. This highlights the importance of considering not just technological features, but also the cognitive experiences of users.

The study also suggests that consumers may have become accustomed to personalization, treating it as a standard feature rather than a distinguishing factor. As a result, its influence on decision-making may be reduced. At the same time, the presence of multiple options and continuous decision-making can lead to mental exhaustion, which has a stronger impact on behaviour.

These findings contribute to a better understanding of consumer behaviour in digital environments. They indicate that simply increasing personalization may not always lead to better outcomes. Instead, platforms need to focus on reducing cognitive overload and making the decision-making process easier for users.

In conclusion, the study highlights the importance of decision fatigue as a key factor influencing purchase decision-making. While personalization algorithms are widely used, their effectiveness may depend on how they are implemented and how consumers interact with them. The findings provide valuable insights for both researchers and practitioners in understanding the balance between personalization and user experience.

2. Theoretical Implication

The findings of this study offer several important theoretical implications in the context of consumer behaviour and digital marketing. The research contributes to the existing body of knowledge by examining the relationship between personalization algorithms, decision fatigue, and purchase decision-making, and by testing how these constructs interact within a digital commerce environment.

One of the key theoretical contributions of this study lies in its examination of Cognitive Load Theory. This theory suggests that individuals have a limited capacity to process information, and when this limit is exceeded, it can negatively affect decision-making. The findings of this study partially support this theory. The significant relationship between decision fatigue and purchase decision-making confirms that cognitive overload plays an important role in influencing consumer behaviour. As consumers are exposed to multiple options and repeated decision-making tasks, their ability to make effective decisions decreases, leading to hesitation or avoidance. This reinforces the relevance of cognitive load in digital shopping environments.

At the same time, the study provides an interesting extension to this theory by showing that personalization algorithms do not significantly contribute to decision fatigue. While it is often assumed that personalized recommendations increase cognitive load by presenting multiple relevant options, the results suggest that personalization alone may not be sufficient to overwhelm consumers. This indicates that cognitive load in digital environments may be influenced by a combination of factors rather than a single element such as personalization.

The study also relates to Ego Depletion Theory, which explains how repeated decision- making can reduce an individual's mental energy over time. The strong relationship between decision fatigue and purchase decision-making supports this theory. It suggests that as consumers continue to evaluate options and make choices, their cognitive resources become depleted, affecting their ability to make decisions effectively. This finding strengthens the theoretical understanding of how mental exhaustion influences consumer behaviour in online settings.

Another important implication is related to the role of personalization in consumer decision- making. Existing literature often highlights the positive impact of personalization in improving customer experience and increasing purchase intention. However, the findings of this study challenge this assumption by showing that personalization does not have a significant direct effect on purchase decision-making. This suggests that the theoretical understanding of personalization may need to be reconsidered. Rather than viewing personalization as a direct driver of behaviour, it may be more appropriate to consider it as a supportive or facilitating factor. Furthermore, the lack of a significant mediating effect of decision fatigue indicates that the relationship between personalization and consumer behaviour is not as straightforward as previously assumed. This highlights the need for future research to explore additional variables that may influence this relationship, such as trust, perceived relevance, or user engagement.

Overall, the study contributes to theory by highlighting the importance of psychological factors, particularly decision fatigue, in shaping consumer behaviour. It also suggests that the impact of technological features such as personalization should be understood in a more nuanced manner. These insights help in refining existing theoretical frameworks and provide a foundation for further research in digital consumer behaviour.

3. Managerial Implication

The findings of this study offer several important implications for managers and practitioners operating in the digital commerce space. As organizations increasingly rely on personalization algorithms to enhance customer experience, it becomes essential to understand how these strategies influence consumer behaviour beyond their intended benefits.

One of the key implications of this study is that personalization alone may not be sufficient to drive purchase decisions. While consumers do perceive recommendations as relevant and tailored, this does not necessarily translate into actual purchase behaviour. For managers, this suggests that personalization should not be viewed as a standalone strategy for increasing conversions. Instead, it should be integrated with other factors such as pricing strategies, trust- building mechanisms, and product quality to create a more holistic customer experience.

Another important implication relates to the role of decision fatigue. The findings clearly indicate that decision fatigue has a significant impact on purchase decision-making. As consumers experience mental exhaustion, they are more likely to delay or avoid making purchases. This highlights the need for digital platforms to focus on simplifying the decision-making process. Managers should consider reducing the number of choices presented to users or organizing options in a more structured manner. Features such as curated recommendations, filters, and comparison tools can help in minimizing cognitive load and making the shopping experience more manageable.

The study also suggests that overexposure to options can negatively impact user experience. Even when recommendations are personalized, presenting too many similar options can lead to confusion rather than clarity. Managers should therefore focus on quality over quantity when it comes to recommendations. Instead of showing a large number of products, platforms can prioritize the most relevant options and present them in a way that is easy to evaluate.

Another implication is related to user interface and experience design. Since decision fatigue is closely linked to cognitive effort, the design of the platform plays a crucial role in shaping consumer behaviour. Simplified layouts, clear categorization, and intuitive navigation can reduce the effort required to process information. This can help consumers make quicker and more confident decisions, thereby improving conversion rates.

The findings also indicate that consumers may have become accustomed to personalization, treating it as a standard feature rather than a differentiating factor. For managers, this means that simply offering personalized recommendations may no longer provide a competitive advantage. Instead, innovation in how personalization is delivered, such as through more meaningful and context-aware suggestions, may be required to create a stronger impact.

Additionally, managers should be cautious about relying too heavily on algorithm-driven strategies without considering the human aspect of decision-making. While algorithms can optimize recommendations based on data, they may not always account for the cognitive limitations of users. Balancing technological efficiency with user comfort is essential in designing effective digital experiences.

Overall, the study highlights the importance of adopting a consumer-centric approach in digital marketing strategies. Managers need to focus not only on what can be recommended, but also on how much information the consumer can effectively process. By reducing cognitive overload and improving the decision-making experience, organizations can enhance both customer satisfaction and business outcomes.

3. Limitations of the Study

While the study provides useful insights into the relationship between personalization algorithms, decision fatigue, and purchase decision-making, it is important to acknowledge certain limitations that may have influenced the findings.

One of the primary limitations of the study is the use of a convenience sampling method. The data was collected from respondents who were easily accessible, which may not fully represent the entire population of online consumers. As a result, the findings may be limited in terms of generalizability and may not accurately reflect the behaviour of all consumer groups.

Another limitation is the reliance on self-reported data. The responses collected through the questionnaire are based on the perceptions and opinions of the respondents. This introduces the possibility of response bias, where participants may not always provide completely accurate or honest answers. Additionally, respondents may interpret questions differently, leading to variation in responses.

The study also focuses on a limited number of variables, specifically personalization algorithms, decision fatigue, and purchase decision-making. While these variables are relevant, consumer behaviour in digital environments is influenced by several other factors such as price sensitivity, brand trust, product type, and urgency. The exclusion of these variables may limit the overall explanatory power of the model.

Another limitation is that the study follows a cross-sectional design, where data is collected at a single point in time. This does not capture changes in consumer behaviour over time or how repeated exposure to personalization may affect decision-making in the long run.

Finally, the study is limited to the digital commerce context and does not consider offline shopping environments. Consumer behaviour may differ across contexts, and therefore, the findings cannot be directly applied to non-digital settings.

Despite these limitations, the study provides a meaningful understanding of the role of decision fatigue and personalization in influencing consumer behaviour.

V. CONCLUSION

The present study aimed to examine the impact of personalization algorithms on consumer decision fatigue and purchase decision-making in digital commerce environments. With the increasing reliance on artificial intelligence and data-driven recommendations, understanding how consumers respond to personalized content has become highly relevant. The study focused on identifying whether personalization simplifies decision-making or contributes to cognitive overload, and how this, in turn, affects purchase behaviour.

The findings of the study indicate that personalization algorithms, although widely used and generally perceived positively by consumers, do not have a significant direct impact on purchase decision-making. This suggests that while personalization enhances the browsing experience and helps users discover relevant products, it does not necessarily influence their final purchasing decisions in a measurable way.

On the other hand, decision fatigue was found to have a strong and significant impact on purchase decision-making. Consumers who experience higher levels of mental exhaustion are more likely to face difficulty in making decisions, delay their purchases, or avoid completing transactions altogether. This highlights the importance of cognitive factors in shaping consumer behaviour in digital environments.

The study also found that decision fatigue does not mediate the relationship between personalization and purchase decision-making, as personalization was not significantly related to decision fatigue. This indicates that the influence of personalization may be more indirect or dependent on other factors not included in the study.

Overall, the research emphasizes that while technological features such as personalization are important, they are not sufficient on their own to influence consumer decisions. Greater attention needs to be given to the cognitive experience of users. Reducing complexity and making the decision-making process easier may be more effective in improving consumer outcomes than simply increasing the level of personalization.

Scope for Future Research

The present study opens up several opportunities for future research in the area of digital consumer behaviour. While this study focused on personalization algorithms, decision fatigue, and purchase decision-making, future research can expand the model by including additional variables such as trust, perceived relevance, user engagement, and brand loyalty. These factors may provide a more comprehensive understanding of how consumers interact with personalized content.

Future studies can also explore the role of different product categories in influencing decision fatigue. Consumer behaviour may vary significantly depending on whether the purchase involves low-involvement products, such as everyday items, or high-involvement products, such as electronics or luxury goods. This could provide deeper insights into how decision fatigue operates in different contexts.

Another area for future research is the use of longitudinal studies to examine how consumer responses to personalization change over time. As users become more familiar with digital platforms, their perception and reaction to personalization may evolve.

Additionally, future research can consider experimental designs to establish stronger causal relationships between variables. Comparing different levels of personalization or varying the number of choices presented to consumers can help in understanding how these factors directly influence decision fatigue and behaviour.

Overall, future research can build on this study to develop a more nuanced understanding of consumer decision-making in digital environments.

REFERENCES

1. A, P., M, S., & Selvi, J. (2025, November 3). Digital seduction: When personalized marketing blurs into personal manipulation—A consumer behavior analysis. https://journals.sagepub.com/doi/abs/10.1177/20438869251394039
2. Asghar, M. M. (n.d.). How ai personalization influences purchase decisions. International Journal of Business, Management & Financial Insight. https://scholarclub.org/index.php/IJBMFI/article/view/128
3. Canarslan, N. Ö. (2025, December 17). The impact of choice overload and decision fatigue on cart abandonment in online shopping. OPUS Journal of Society Research. https://dergipark.org.tr/en/pub/opusjsr/article/1743550
4. Deepa, V., Halder, S. R., Kalhapure, B., Sonkamble, S., & Patel, C. (2025, July 1). Ai and consumer psychology: Personalization, ethical nudging, and digital decision-making. EBSCOhost. https://openurl.ebsco.com/EPDB%3Agcd%3A13%3A12716221/detailv2?sid=ebsco%3Aplink%3Ascholar&id=ebsco%3Agcd%3A190294125&crl=c&link_origin=scholar.google.com
5. Dek, H., & Ibrahim, N. (n.d.). Artificial Intelligence in Digital Marketing: Impacts on consumer decision-making and privacy concerns. Journal of Policy Options. https://resdojournals.com/index.php/jpo/article/view/433
6. Du, H. S., Chen, T., & Ke, X. (n.d.). Personalized or pressurized? the influence of ai-powered personalized recommendation triggered information stressor on consumers' discontinuance purchase behavior. https://www.tandfonline.com/doi/abs/10.1080/10447318.2025.2598452
7. Dubazana, & Nolwazi, A. (2024, November 4). The Influence of Algorithmic Technologies on Perceptions of Autonomy in Consumer Decision-Making. https://www.proquest.com/openview/d6ee447e39465cbe478bee4563a965b0/1?pq-origsite=gscholar&cbl=2026366&diss=y
8. Hu, M. (2026, January 9). Effectiveness of AI-based personalized recommendations in reducing choice overload on e-commerce platforms. NORMA@NCI Library. https://norma.ncirl.ie/9082/
9. Hussain, S. R. (2025, April 24). The Personalization Paradox: When AI Stops Helping and Starts Overwhelming. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5223317
10. The impact of AI-driven recommendation systems on consumer behaviour and decision making: A study of personalization and privacy concerns. Journal of International Commercial Law and Technology. (2026, January 16). https://www.jiclt.com/article/the-impact-of-ai-driven-recommendation-systems-on-consumer-behaviour-and-decision-making-a-study-of-personalization-and-privacy-concerns-324/
11. Navigating the filter bubble: A pill for hyperpersonalization: Business & management book Chapter | IGI Global Scientific Publishing. (n.d.-a). https://www.igi-global.com/chapter/navigating-the-filter-bubble/372413
12. Psychological triggers in online shopping: The influence of scarcity, urgency, and personalization on consumer buying behavior | The Critical Review of Social Sciences Studies. (n.d.-b). https://thecrsss.com/index.php/Journal/article/view/443
13. Run: The impact of recommendations agents in consumers' purchasing decisions and satisfaction. (n.d.-c). https://run.unl.pt/handle/10362/184673

14. Rushikesh, S., & Gaikwad, F. (n.d.). Impact of AI-powered recommendation systems on the online purchasing B. Taylor & Francis. https://www.taylorfrancis.com/chapters/edit/10.1201/9781003755005-32/impact-ai-powered-recommendation-systems-online-purchasing-behavior-millennials-urban-india-focus-decision-fatigue-gender-trust-rushikesh-gaikwad-semila-fernandes
15. Sathish, P., Avula, S. R., & Channabasava, C. (2026, January 23). AI-powered personalization and its impact on sustainable consumer behaviour in digital marketing. ITM Web of Conferences. https://www.itm-conferences.org/articles/itmconf/abs/2026/01/itmconf_etmis2025_01001/itmconf_etmis2025_01001.html
16. Trivedi, B. (2025, August 7). Avoiding Personalization Fatigue: A Heuristics-Based Framework for Retail Digital Commerce. https://www.researchgate.net/profile/Bhargav-Trivedi-2/publication/394866778_Avoiding_Personalization_Fatigue_A_Heuristics-Based_Framework_for_Retail_Digital_Commerce/links/68ac41b86327cf7b63d935be/Avoiding-Personalization-Fatigue-A-Heuristics-Based-Framework-for-Retail-Digital-Commerce.pdf
17. Understanding customer responses to ai-driven personalized journeys: Impacts on the customer experience. (n.d.-d). https://www.tandfonline.com/doi/full/10.1080/00913367.2025.2460985
18. Zhuang, Z. (n.d.-a). The impact of personalized recommendation algorithms on consumers' purchasing decisions. https://www.researchgate.net/publication/399179283_The_Impact_of_Personalized_Recommendation_Algorithms_on_Consumers'_Purchasing_Decisions
19. Zhuang, Z. (n.d.-b). The impact of personalized recommendation algorithms on consumers' purchasing decisions. Journal of Education, Humanities and Social Sciences. https://drpehss.com/index.php/ojs/article/view/29