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THE IMPACT OF ARTIFICIAL INTELLIGENCE ON CONSUMER BEHAVIOR IN FASHION RETAIL: A STUDY IN OMAN

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The Impact Of Artificial Intelligence On Consumer Behavior In Fashion Retail: A Study In Oman

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Abstract

This study investigates the influence of Artificial Intelligence (AI) technologies on consumer behavior and subsequent shopping patterns within the context of Oman's Fashion Retail Sector (FRS). Leveraging the capabilities of AI specifically Enhanced Consumer Service (ECS), Product Discovery (PD), Phygital/Touchpoint Beacons (PTB), and Augmented Reality (AR) the research aims to empirically model their combined impact on purchase decisions. Data were collected through a quantitative survey from 291 valid consumer responses, predominantly comprising young (21-30 years), highly educated individuals who identified as Promotion-driven and Trend-influenced shoppers. Using Structural Equation Modeling (SEM), the findings confirmed that all four AI-driven technological drivers exert a strong, positive, and statistically significant relationship with consumer shopping patterns, thereby validating the research framework. Crucially, the analysis of total effects revealed that AI's impact is most pronounced in facilitating Enhanced Consumer Service (0.5142), suggesting its primary immediate value lies in improving service interaction rather than merely simplifying product search. The study concludes that AI serves as a transformative tool for FRS retailers in Oman, necessitating strategic investment in omnichannel integration and personalized service technologies to meet the demands of the tech-savvy, cost-conscious consumer base. The results provide actionable insights for practitioners seeking to optimize their AI integration strategies for competitive advantage in the local market.

Keywords: artificial intelligence, fashion retail, consumer behavior, enhanced service, augmented reality.

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

Significant transitions have been seen in the global fashion retail sector, followed by a rapid adoption and development of Artificial Intelligence (AI). AI capabilities embedded into natural language processing (NLP), machine learning (ML), predictive analytics and computer vision (CV) has tailored changes in opinion in the way businesses optimize operations, deliver value and interact with customers (Ojika et al. 2021). Fashion outlets like New York, Tokyo and Paris have seen this blooming transformation. They are respecting the AI that boosts their customer experiences. Virtual try-ons, predictive fashion trend forecasting and AI-powered chatbots provides real-time recommendations to customers. (McKinsey & Company, 2024). Retailers have been equipped with these technologies to deliver customized shopping journeys, seamlessly consolidating offline and online channels.

AI has achieved immense economic potential. As per the PwC (2023) data, AI contribution has been anticipated around \$900 billion by 2026 across the global economy and an amazed \$15.7 trillion market value by 2030. The market valuation of AI has been anticipated to extend up to \$1,394.3 billion by 2029 across the sole retail industry, while the CAGR rate projected at 40.8% forward from 2024 (National-Qualification-Register, 2023). This aggressive market traction has been contributed to AI's proficient to highly customize shopping, empower supply chain efficiency, enhance customer engagement solutions and optimize pricing (Goti et al., 2023). As an outcome, AI has contributed more than a supplementary tool, instead emerged as a strategic imperative for retail competitiveness and survival.

The Fashion retail industry of has seen rapid expansion, yet remained a challenging domain, with a market value projected at \$1.33 billion in 2024, however the domain has seen comparatively lower traction unlike the global market (Statista, 2023). The domain has been classified with unpredictable customer demand, small margins, fierce competition and poor customer loyalty (Tahir, 2021). Omani fashion retailers have growingly integrated AI technologies regardless of the challenges encountered, to recompose customer experiences and embrace business outcome. International fashion businesses functioning in Oman, including H&M and Zara, have integrated AI-based solutions into business operations spanning from augmented reality (AR)-based smart mirrors towards personalized fitting experiences to inventory management based on computer vision (Inditex, 2019; Todd, 2022). For instance, Zara has established AI-powered real-time analytics and recommendation engines for both online and in-store experiences; on the other hand, H&M derived d AR mirrors and predictive analytics to tailor customized outfits. Demonstration of these innovations conveys the AI potential to significantly impact customer shopping behavior within the fashion retail sector in Oman.

At a consumer level, AI is altering traditional shopping patterns by creating a “Phygital” experience a seamless combination of physical and digital retail (Iannilli & Spagnoli, 2021). Consumers increasingly expect hyper-personalized recommendations, virtual assistance, omnichannel shopping convenience, and cost-efficient solutions. AI-powered personalization tools, recommendation systems, AR try-ons, and AI-driven chatbots are changing the way consumers in Oman interact with fashion brands. However, despite these global and local advancements, the academic exploration of AI’s impact on consumer behavior in Oman’s fashion retail sector remains limited.

1.2 Research Problem Statements

Although AI adoption in fashion retail is advancing globally, there is insufficient empirical research investigating its impact on consumer behavior in Oman. Much of the existing literature focuses on technologically advanced markets in Europe, North America, and East Asia, leaving a gap in understanding how AI-driven retail strategies influence consumer decision-making in emerging economies such as Oman. This creates several critical research gaps that necessitate systematic investigation. First, while AI technologies such as personalization engines, AR, and omnichannel strategies are recognized globally as drivers of consumer engagement, their specific influence on Omani consumers who may have distinct cultural preferences, shopping behaviors, and budget-conscious tendencies remains largely unexplored. Understanding how consumers in Oman respond to personalization, technological adoption, and digital touchpoints is vital for tailoring AI applications effectively in the local market (Al Busaidi, 2024; 6Wresearch, 2025). The role of AI in reshaping consumer service delivery and product discovery in Oman's retail landscape is under-researched. Although international retailers like Zara and H&M demonstrate the successful integration of AI in their Omani outlets, little is known about how these technological innovations influence consumer satisfaction, loyalty, and purchasing decisions (Nguyen, 2025). Retailers require empirical evidence to determine whether AI-driven interventions resonate with local shoppers or whether cultural and behavioral nuances necessitate modified approaches.

The transformative effects of AI in facilitating Phygital experiences, augmented reality engagement, and omnichannel integration in Oman remain unaddressed in academic research (Pangarkar et al. 2022). The growing use of AR smart mirrors, AI chatbots, and touchpoint beacons globally indicates a shift in consumer expectations toward more interactive and immersive experiences (Chaudhuri et al. 2024). However, the extent to which Omani consumers embrace or resist such innovations has yet to be examined. However, an urgent necessity to investigate mediating role of AI into customer shopping outcomes and customer drivers (tech-savviness, personalization-seeking, and budget-consciousness) in fashion retail sector of Oman has been observed. Irrespective of international discourses recommended that AI potential shape consumer loyalty, brand engagement and decision-making (Kiang, 2024), empirical justification in the favour of Oman seen absent. Omani fashions retailers can encounter uncertainty to invest in AI technologies, especially when ensuring their alignment with customer expectations, if not these insights are adhered.

In a nutshell, the research scope has lied into the restricted scholarly comprehension of AI potential to shape customer attitudes in the fashion retail sector of Oman. The poor adoption of region-centric discourses has tailored a knowledge gap, which held back retailers to fully realize AI's ability to influence customer preferences, loyalty and shopping patterns. Hence, this research has sought to address this gap by exploring AI's influence on Omani customers via like technology adoption, personalization, budget considerations, omnichannel strategies, innovative tools (Phygital experiences and AR), and service enhancement. By addressing these gaps, the study contributes to both academic literature and practical retail strategy. It provides a framework for understanding AI's role in consumer behavior transformation in Oman and offers actionable insights for fashion retailers to design more effective, consumer-centric, and competitive AI-driven retail strategies.

1.3 Research Questions and Objectives

1.3.1 Research Questions

Building on the limited understanding of AI's impact on consumer behavior in Oman's FRS, the current research is guided by the following key questions:

RQ #1: What is the influence of AI in Oman's FRS, with a specific focus on personalization-seeking behavior, adoption of technology-driven solutions, omnichannel approach, tech-savvy, and budget-conscious dimensions?

RQ #2: What is the transformative influence of AI in Oman's FRS, considering enhanced consumer service, product discovery, Phygital & touchpoint beacons, and Augmented Reality?

RQ #3: What is the impact of personalization-seeking behavior, adoption of technology-driven solutions, omnichannel approach, tech-savvy, and budget-conscious on consumer behavior within Oman's FRS, with AI playing a central role?

RQ #4: What is the influence of enhanced consumer service, product discovery, Phygital & touchpoint beacons, and Augmented Reality on consumer shopping patterns within Oman's FRS, with AI playing a central role?

1.3.2 Research Objectives

To address the above-mentioned research questions, the study aims to achieve the following objectives: The current study seeks to understand the impact of AI on consumer behavior in Oman's fashion retail sector. The specific research objectives are clearly and precisely set, and all objectives lead to predetermined goals within the context of FRS in Oman. During the formulation of research objectives, several key factors were identified and given extra attention: personalization-seeking behavior, the adoption of technology-driven solutions, omnichannel strategies, tech-savvy consumer environments, and budget-conscious considerations. These are critical aspects for understanding consumer behavior in FRS in Oman. Moreover, the objectives also highlight the effect of AI on other vital elements, such as increased consumer service, efficient product discovery, Phygital and touchpoint beacons, and Artificial Intelligence powered by Augmented Reality based on consumer shopping behavior.

RO #1: The purpose of this research is to investigate the impact of AI on the following factors: personalization-seeking behavior, adoption of technology-driven solutions, omnichannel approach, tech-savviness, and budget consciousness. The research aims to examine how AI influences consumers' preferences for shopping carts, their willingness to adapt to new technology, and the factors that shape their shopping behavior.

RO #2: This objective examines how AI can enhance consumer service, product discovery, phygital experiences, touch point beacons, and augmented reality (AR) applications.It has investigated the way in AI possess the potential to elevate an overall consumer experience, spanning from better service delivery towards leveraging ease in product innovation. It has also elaborated further discussion on the utilization of Phygital interactions and AR, in the way it makes seamless consolidation of digital and physical experiences with respect to consumers.

RO #3: Investigate the mediating effect of consumer behavior on the relationship between key dimensions (personalization-seeking, technology adoption, omnichannel expectations, tech-savviness, and budget-consciousness) and AI integration within Oman's FRS.

RO #4: Investigate the mediating role of consumer shopping patterns in the relationship between drivers (enhanced service, efficient discovery, phygital experiences, AI/AR engagement) and successful AI implementation in Oman's fashion retail organizations.

CHAPTER TWO: LITERATURE REVIEW

The integration of Artificial Intelligence (AI) into fashion retail is rapidly transforming consumer behavior, retail operations, and competitive strategies worldwide. AI-powered tools such as personalization engines, predictive analytics, augmented reality (AR), and omnichannel platforms have been extensively examined in global contexts (Harreis et al., 2023; McKinsey & Company, 2024). However, limited research has focused on emerging markets such as Oman, where cultural preferences, budget-consciousness, and evolving digital ecosystems may uniquely shape AI adoption. The already established scholarly discourses relevant to the research structured, questions and around key themes have been reviewed in this chapter.

2.1 AI and Personalization-Seeking Behaviour

AI boom into the digital shopping experience has made surprising transformation in the fashion retailing premises by delivering customers a personalized and dynamic shopping experience. Personalization leveraged by AI potential has made growing traction in machine learning algorithms, computer vision, predictive analytics and natural language processing (NLP), to review customer attitude and contribute tailored offerings (Band et al. 2024). A vital role has been demonstrated by these technologies to embrace customer satisfaction, boosting exposure with fashion brands and driving conversion rates. Recommendation engines refer to the most significant exposure of AI into fashion shopping upon internet premises (Chakraborty et al. 2021). Recommendation engines investigate purchase behaviour, customer preferences, current interactions and browsing habits, to suggest goods that are compliance to individual choices (Pleskach et al. 2023). Reviews have shown that recommendation based on AI algorithm can derive grown conversion rates, as customers mostly prefer to buy products that are tailored to their past interactions (Vallabhaneni et al. 2024; Jancy & Muthukumaravel, 2025). Edberg (2025) has introduced that consumers mostly accept to AI-based recommendations when those are non-intrusive and contextually ideal. This has also emphasized the imperative for ideally-tailored recommendation algorithms. Such personalization measures have been occasionally anticipated towards personalization remained underexplored. The cultural preferences, differing expectations of operation and privacy concerns might model the degree to which personalization impact on purchase intentions (Taufiq-Hail et al. 2023).

2.2 Technology Adoption and Consumer Behaviour

Technology has significantly reshaped the digital landscape, transformed consumer behavior and fuelled the rise of e-commerce. The widespread use of the internet and mobile devices has enabled consumers to shop anytime and anywhere, accelerating the shift from traditional retail to online platforms. Today, mobile and internet purchases account for over half of retail sales, resulting in declining revenues for brick-and-mortar outlets while boosting online channels. In Oman, research on social commerce and AR adoption indicates that hedonic value and ease of use significantly affect online shopping intentions (Al Busaidi, 2024). Businesses must therefore adapt their strategies to remain competitive, leveraging digital platforms to engage customers more effectively (Nishat, 2024). While online shopping offers convenience, variety, and cost benefits (Srivastava & Thaichon, 2023), it also presents challenges. Peters et al. (2025) explored that the lack of sensory interaction such as touching or smelling products creates barriers to consumer trust and engagement, underscoring the need for innovative solutions in e-commerce (Horakova et al., 2022; Jiang et al., 2021).

2.3 Omnichannel Approach

Omnichannel refers to the integration of all communication and sales channels a company uses to interact with its customers, aiming to provide a seamless and consistent shopping experience regardless of the channel. Unlike multichannel approaches, where channels operate independently, omnichannel ensures that online and offline touchpoints work together harmoniously (Lorenzo-Romero et al., 2020). Companies sell their products through direct channels, such as physical stores at sale through the telephone, and indirect channels, where the different intermediates assist in selling to the ultimate consumer , for example, travel agencies, when it sells hotel services (Rangel & Rivero, 2014). Thanks to the evolving use of digital channels, consumer behavior has transformed tremendously, now they check multiple touchpoints before a purchase, including research, comparisons and reviews. There are now different types of consumers, such as people who Research and then Test and Buyer (RTB) and Research Online, purchase offline (ROPO) and showroomers. Moreover this has happened this behaviour. Thus, integrated omnichannel strategy is a need of the hour. Unbroken integration of offline and online services has established sameness in availability, service quality and pricing through same day delivery, augmented reality interfaces, click & collect (Smith,2024). Studies have proven that through an integrated channel strategy, operational efficiency, profitability and customer satisfaction can be embraced which have become essential to compete in various retail sectors. (Rolando et al., 2024).

2.4 Tech-Savviness

Recently the fashion retail sector has been benefiting due in part to using cellular communication and other equipment to assist. The most impressive increase in customer interraction has been with AI powered charbots and virtual assistants this last year (Kautish et al., 2023). Good customer support is easily had with some of the new technology accepting the support on the spot of what the customer would like to know (Morotti et al., 2022). Talking to these apps and machines by thier NLP alorithms let the conversation flowing at normal with the customer so they get there questions answered just the same way(Keerthiga, 2022). Outside of just answering letters, most AI formats have really built up customer trust and loyalty by trying to change the way the company and consumer preload, offer style suggestions, and even helps out with purchasing things. By putting AI technology into those shopping assistants, Consumer journeys are altered and people see purchasing experience as nice, convienent, and fast.2.5 Budget-Conscious Behaviour

The consumer preferences have influenced growingly by budget consciousness into the iverse fashion retail sector (FRS), which also been remained a central condition of shopping behavior (Takao et al. 2020). Given that customers often experiece a dynamic wave of fashion choices, they frequently shape their shopping decisions based on financial considerations, with steer choice of customers to balance style aspirations and affordability (Qazzafi, 2019). This increasing attention on value-driven consumption has elaborated the strategical significance that can respond to both quality expectations and price sensitivity. Given the environment, AI algorythms generously introduce transformative opportunities. The introduction of preductive analytics has enabled AI to recommend cost-effective substitues, provide tailored offers and identify discounts that adhere to customer budgets (Pupillo, 2019).

2.6 Enhanced Consumer Service

AI integration within business operations has made notable transitions of customer shopping patterns, especially contextualizing the vulnarable context of customer service. Tools embedded with AI potentials, such as virtual assistants and chatbots are enabled to offer real-time and continuous assistance, allowing customers to promptly resolve concerns and inquiries (Kautish et al., 2023; Morotti et al., 2022). The 24/7 availability of these tools can embrace convenience, enforce seamless shopping experiences, and leverages higher consumer satisfaction (Shirkhani et al., 2023; Harreis et al., 2023). Apart from advocating above perks, AI-powered mechanisms further compliments on the accessibility and accuracy of product insights by seizing reliable data out of diverse sources. In this regard, the reduction of post-purchase uncertainty and dissatisfaction gets facilitated (Mohammadi & Kalhor, 2021). These inventions have demonstrated transformative role of AI to empower quality of consumer service via efficiency and personalization. Despite confrmation guranteed from global studies, little acknowledgemnt enlightened around their reception in the fashion retail sector of Oman. This study has investigated the way in Omani customers view personalized AI recommendations and round-the-clock assistance, given their strict cultural influence.

2.7 Increased Product Efficiency

AI-powered solutions have revolutionized product innovation within the fashion retail sector sector by tailoring customized-consumer experiences via advanced algorithms. Hybrid recommendation infrastructures, deep learning (DL) frameworks, including RNNs and CNNs, pattern recognition and natural language processing (NLP) have catered the structural evaluation of purchase history, consumer behavior, demographic insights and browsing activity (Waciira & Thomas, 2023; Xu et al., 2022; Laaziz, 2020). Integrating massive proportion of customer data have enabled these infrastructures to introduce highly reliable product recommendations, embracing satisfaction and convenience (Björkman et al., 2023). This data-driven process has accelerated product discovery alongside minimizing the intention necessitated to steer extensive catalogues. This has allowed customers to emphasize on goods that typically comprise with their purchasing choices (Rossi, 2020; Bellini et al., 2023). The reviews made in global sphere have confirmed the effectiveness of these mechanisms, while this study has investigated their applicability in FRS of Oman, explored their approach to deliver AI-powered recommendations and shape unique purchasing behaviour and consumer satisfaction.

2.8 Phygital & Touchpoint Beacons

FRS has expreinecd a profound transition via the unification of digital and physical experiences, which often refers to the term of "Phygital." This transition has been leveraged with the contactless innovations along with advanced mobile technologies, including QR codes, RFID, Beacons and NFC. These technologies, altogether have embraced interactivity and convenience (Iannilli & Spagnoli, 2021). Phygital retail has bridged the outdated brick-and-mortar stores in the company of online engagement, on the other hand touchpoint beacons deriving a central role. These AI –powered IoT devices have enabled shoppers connection with smartphones through Bluetooth Low Energy (BLE). It has enabled personalized offers, in-store navigation and tailored recommendations. These applications have delivered a systematic model to comprehend potential of Phygital innovations to reconfigure shopping patterns. The current research has examined the effort of Oman's fashion retail sector to imply these innovations and consumers' agility to into this hybrid retail experience. This can deliver a detailed insight given the Middle Eastern perspective (Iannilli & Spagnoli, 2021).

2.9 Augmented Reality and Immersive Shopping

The consolidation of AR and AI have revolutionized fashion retail with the benefits of personalized, data-driven and immersive shopping experiences (Pupillo, 2019; Hilpert & Zumstein, 2023). The virtual try-ons are key innovation in this regard; allowed customers to virtually experiment with clothing, return rates and undermine fitting room reliance (Nautiyal et al., 2021; Lagė & Ancutienė, 2019). The recommendation systems powered by AI technology can interpret preferences using natural language processing and deep learning. This further gets visualized by AR on the consumer and increase satisfaction and confidence (Xu et al., 2022). In-store phygital experiences, including mobile apps, touchpoint beacons and AR mirrors have unified digital convenience even in physical engagement (Iannilli & Spagnoli, 2021). On the other hand, AR and AI can optimize inventory, while virtual fashion shows and catalogs democratize trends. This research has explored potential of these technologies to shape customer behavior in the fashion retail sector of Oman.

2.10 Theoretical Perspectives

Several consumer behavior theories have been applied by this research to interpret AI potential to influences shopping patterns into the fashion retail sector (FRS) of Oman. The Technology Acceptance Model (TAM) has been interpreted to comprehend importance of ease of use and perceived usefulness in driving customer adaptability of AI-powered instruments like recommendations, chatbots and virtual try-ons. Justifying the concept above, the Unified Theory of Acceptance and Use of Technology (UTAUT) has emphasized on social influence, behavioral intention, facilitating conditions and unifyed several models to seize diferent conditions impacting AI adoption (Gao & Liang, 2025). The Theory of Planned Behavior (TPB) has also elaborated importance of subjective norms, perceived behavioral control and attitudes to influence consumers' willingness (La Barbera & Ajzen, 2020) and to engage AI within FRS. In addition, the Consumer Decision-Making Process model has demonstrated AI potential to alter problem recognition, evaluation, post-purchase behaviors and information search (Panwar et al. 2019). Therefore, the Consumer Value Theory has justified significance of AI-driven personalization to embrace satisfaction, loyalty and perceived value (Woodruff, 1997), and contributed an integrated model.

2.11 Operational Definition Table

Variable	Operational Definition	Null Hypothesis (H0)	Alternative Hypothesis (H1)
Personalization-Seeking Behavior	The extent to which consumers desire customized shopping experiences, including AI-based recommendations, tailored promotions, and individualized product suggestions.	H01: There is no significant relationship between AI-driven personalization and consumer behavior in Oman's FRS".	H1a: There is a significant positive relationship between AI-driven personalization and consumer behavior in Oman's FRS.
Adoption of Technology-Driven Solutions	The willingness of consumers to embrace AI-powered tools such as chatbots, AR applications, and recommendation systems to enhance shopping experiences.	H02: There is no significant relationship between consumer adoption of AI technologies and shopping patterns in Oman's FRS.	H1b: There is a significant positive relationship between consumer adoption of AI technologies and shopping patterns in Oman's FRS.
Omnichannel Approach	Integration of physical and digital retail channels (e.g., click & collect, AR mirrors, beacons) to provide seamless shopping experiences.	H03: There is no significant relationship between omnichannel strategies and consumer shopping behavior in Oman's FRS.	H1c: There is a significant positive relationship between omnichannel strategies and consumer shopping behavior in Oman's FRS.
Tech-Savviness	The degree of consumer familiarity and comfort in using AI-powered applications, digital platforms, and interactive retail technologies.	H04: Tech-savviness has no significant effect on AI adoption and consumer behavior in Oman's FRS.	H1d: Tech-savviness has a significant positive effect on AI adoption and consumer behavior in Oman's FRS.

Budget-Consciousness	The extent to which financial considerations, cost savings, and affordability influence consumer decision-making in AI-enabled retail.	H05: Budget-consciousness has no significant relationship with AI-enabled shopping decisions in Oman's FRS.	H1e: Budget-consciousness has a significant relationship with AI-enabled shopping decisions in Oman's FRS.
Enhanced Consumer Service	Delivery of personalized, 24/7 support through AI-powered chatbots and virtual assistants that improve customer satisfaction.	H06: AI-enabled consumer service has no significant impact on consumer satisfaction and shopping behavior in Oman's FRS.	H1f: AI-enabled consumer service has a significant positive impact on consumer satisfaction and shopping behavior in Oman's FRS.
Product Discovery	AI's role in enabling efficient, relevant, and tailored product search and recommendations for consumers.	H07: AI-powered product discovery has no significant effect on consumer shopping patterns in Oman's FRS.	H1g: AI-powered product discovery has a significant effect on consumer shopping patterns in Oman's FRS.
Phygital & Touchpoint Beacons	Use of IoT-enabled AI beacons to deliver in-store navigation, promotions, and interactive engagement.	H08: Phygital experiences and touchpoint beacons have no significant influence on consumer shopping patterns in Oman's FRS.	H1h: Phygital experiences and touchpoint beacons have a significant positive influence on consumer shopping patterns in Oman's FRS.
Augmented Reality (AR)	Technology overlaying digital elements onto real-world fashion items, enabling virtual try-ons and immersive experiences.	H09: Augmented Reality has no significant impact on consumer purchase decisions in Oman's FRS.	H1i: Augmented Reality has a significant positive impact on consumer purchase decisions in Oman's FRS.
Consumer Behaviour / Shopping Patterns (Dependent Variable)	The observable buying decisions, loyalty patterns, and preferences of consumers shaped by AI adoption in fashion retail.	H010: AI adoption has no significant influence on consumer shopping patterns in Oman's FRS.	H1j: AI adoption has a significant influence on consumer shopping patterns in Oman's FRS.“

CHAPTER 3: METHODOLOGY

3.1 The Conceptual Framework for the Study

The conceptual framework is structured as a complex mediation model designed to test the influence of various technological inputs on business outcomes, specifically in the fashion retail sector. At its core, the model hypothesizes that the nine dimensions of Artificial Intelligence Integration (IVs) such as Personalization-seeking behavior, Omnichannel, and AI-powered by Augmented Reality do not just directly impact Retail Sales Performance (RSP), but that this relationship is significantly channelled, or mediated, through two critical consumer-level responses: Consumer Behavior (CB) and Consumer Shopping Patterns (CSP).

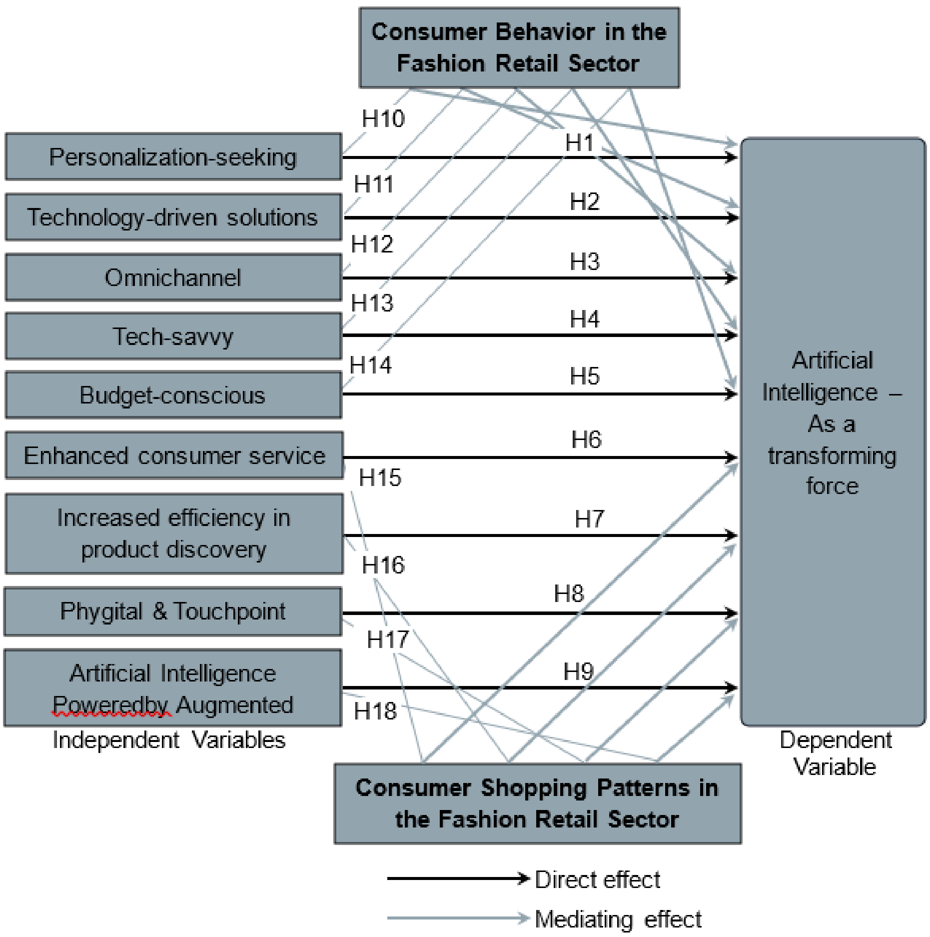

Figure 1: Conceptual Framework

The model suggests that the effect of specific AI technologies on sales performance is not merely direct, but largely flows through changes in consumer responses and transactional habits, thereby providing a more detailed, actionable understanding of AI's strategic value in the fashion industry.

3.2 Research Philosophy

The study adopted the Positivist Research Philosophy, which treats social phenomena as measurable and observable facts (Maretha, 2023). This philosophical stance necessitated the use of rigorous, scientific methods to test theoretical propositions and establish causal relationships between variables. This Positivist approach ensured the rigorous, quantitative testing of hypotheses to establish causal effects in the market.

3.3 Research Approach

Aligning with Positivism, a Deductive Research Approach was employed. This approach started with existing theories (Hall et al. 2023) suggesting AI features like personalization and augmented reality influence consumer purchasing decisions and systematically formulated specific hypotheses for empirical testing within the study's context. This allowed the research to move from general theory to specific, measurable findings concerning the Omani Fashion Retail Sector (FRS).

3.2 Research Design

A Mixed-Method Research Design was implemented to provide a comprehensive and robust investigation (Nanthagopan, 2021). The design primarily relied on a Quantitative Research Approach to test hypotheses against a large dataset (Fischer et al. 2023), followed by a supplementary Qualitative Case Study Method for in-depth validation and contextualization (Hancock et al. 2021). The quantitative component used a cross-Sectional time horizon, meaning data was collected at a single point in time (Maier et al. 2023) to capture consumer attitudes and perceptions towards AI integration at that specific juncture. The qualitative component, utilizing the case study method (n = 27), focused on gaining managerial insights into how fashion retailers in Oman were actually applying AI, thereby enriching the interpretation of the statistical results.

The current study employs a confirmatory and exploratory research design, chosen for its alignment with a mixed-methods research framework.The confirmatory research design facilitates hypothesis testing to ascertain significant relationships (Osman et al. 2022) between the IVs and the mediating influence of consumer behavior and consumer shopping patterns, which are impacted by AI, thereby directly addressing the study's research questions and validating the overall research outcomes. The overall strategy was aimed at ensuring that the findings were both statistically significant and practically relevant.

3.3 Data Collection Method

Quantitative data was gathered via a structured online survey utilizing a 7-point Likert scale (Russo et al. 2021) on nine AI variables, complemented by qualitative case studies. This mixed-method approach, while powerful, risks superficial insights if the survey is not meticulously planned. Clarity of purpose and using appropriate closed-ended questions are essential to transform respondent feedback into meaningful, unbiased research findings (Komildjanovna, 2024). A pilot study was conducted (Kunselman, 2024) with 30 participants, of whom 21 completed the survey. Conducted at six fashion retail outlets in the Mall of Oman, the pilot tested survey clarity, feasibility, and responsiveness across devices. Findings enabled refinement of question design, ensured accessibility, and enhanced the reliability of the finalized survey for the main research.

3.4 Population and Sampling

The research population for this study comprises consumers of fashion retail brands in Oman, as they represent the ultimate end-users whose perceptions and behaviors significantly shape the effectiveness of AI adoption in the fashion retail sector (FRS). Focusing on consumers ensures that insights are drawn directly from those most influenced by AI-driven personalization, service, and shopping innovations. The population age range of 21–45 years was selected, as this demographic accounts for approximately 44.81% of Oman's population of 4.9 million and is highly engaged with technology. To determine an appropriate sample, Krejcie and Morgan's method was employed (Kharuddin et al. 2020). Using the chi-square formula at a 95% confidence level, with an estimated population portion of 0.5 and accuracy of 0.05, the sample size was calculated as 291 respondents. This statistically significant sample allows reliable insights into how AI affects consumer behavior and shopping patterns in Oman's FRS.

3.5 Data Analysis

Data analysis in this study was conducted using SPSS software to ensure accuracy and reliability (Jain & Sengar, 2024). Descriptive statistics were applied to summarize the data and identify patterns (Alabi & Bukola, 2023), while Pearson's correlation and regression analyses examined the relationships between independent and dependent variables (Selvamuthu & Das, 2024). Results were presented visually through graphs and tables for better interpretation. To further ensure precision, a validation process was employed to detect and correct inconsistencies within the dataset. For data collection, the study used SurveyMonkey, a flexible online platform (Rea et al. 2022) that supports diverse question formats, including Likert scales, and offers real-time response tracking with strong data security. Despite its strengths, the research is limited by reliance on self-reported data, which may introduce bias, and its focus on Oman's fashion retail sector, restricting generalizability. Cultural and regional variations may yield different outcomes, and future research should adopt broader, geographically diverse samples and integrate objective measures alongside self-reports.

CHAPTER 4: RESULTS

4.1 Introduction and Synopsis

This chapter analyses survey data from 291 respondents to examine AI's influence on consumer behaviour in Oman's FRS. Using descriptive and inferential statistics, it tests proposed hypotheses, exploring relationships among independent variables, mediators, and the dependent variable. The analysis highlights consumer behavior, shopping patterns, and mediating effects, offering evidence-based insights into AI's transformative retail impact.

4.2 Reliability and Validity Test

To assess the reliability and internal consistency of the survey instrument, we conducted several statistical tests. A total of 283 valid cases (97.3 %) were included in the analysis, with 8 cases (2.7 %) excluded via listwise deletion. This high rate of valid responses indicates strong data retention and minimal loss due to missing values. Across the 15 items used in the scale: the average item means ranged from 2.466 to 2.703, with a mean of 2.575, yielding a modest range (0.237). Item variances varied from 0.323 to 0.489, with inter-item covariances between –0.023 and 0.128, and inter-item correlations spanning –0.061 to 0.350. These figures show reasonable dispersion and association among items without extreme variability. The Cronbach's Alpha for the 15 items was 0.700, with a standardized-items alpha of 0.701. While this value is often considered a minimal acceptable threshold, it suggests that the scale has satisfactory internal consistency for exploratory analysis. The ANOVA decomposition shows between-people variance (311.503 over 282 df) and within-items variance (19.807 over 14 df), with the Cochran's Q statistic equal to 59.181 ($p < 0.001$). The grand mean was 2.57, and the residual mean square was 0.331. The significant Cochran's Q underscores that variance between items is nontrivial, supporting the reliability of item distinctions.

Table 1: Case Processing Summary

		N	%
Cases	Valid	283	97.3
	Excluded	8	2.7
	Total	291	100.0
Listwise deletion is based on all variables in the procedure.			

Of the 291 cases, 283 (97**.3 %)** were valid and retained for analysis, while 8 cases (2.7 %) were excluded via listwise deletion across all variables. This high retention rate supports the robustness of the dataset for subsequent analysis.

Table 2: Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	2.575	2.466	2.703	.237	1.096	.005	15
Item Variances	.382	.323	.489	.166	1.515	.002	15
Inter-Item Covariances	.052	-.023	.128	.152	-5.466	.001	15
Inter-Item Correlations	.135	-.061	.350	.411	-5.743	.007	15

Table 2 presents the summary statistics for 15 survey items. The average of item means is 2.575, with values ranging only slightly between 2.466 and 2.703 (range = 0.237), indicating relatively stable item responses. Item variances lie between 0.323 and 0.489, showing moderate spread in responses. Inter-item covariances range from –0.023 to 0.128, and inter-item correlations span –0.061 to 0.350, suggesting varying degrees of positive association among items. Overall, items demonstrate modest variability and correlation neither excessively redundant nor wholly independent.

Table 3: Reliability Analysis

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.700	.701	15

Table 3 shows a Cronbach's Alpha of 0.700, and 0.701 when items are standardized, across 15 items. These values indicate acceptable internal consistency for exploratory research, suggesting that the items reliably measure the intended construct with moderate reliability.

Table 4: ANOVA with Cochran's Test

		Sum of Squares	df	Mean Square	Cochran's Q	Sig
Between People		311.503	282	1.105		
Within People	Between Items	19.807	14	1.415	59.181	.000
	Residual	1306.193	3948	.331		
	Total	1326.000	3962	.335		
Total		1637.503	4244	.386		
Grand Mean = 2.57						

Table 4's Cochran's test shows significant variance across items. Between-items variance is 19.807 (df = 14), yielding Cochran's Q = 59.181 with $p < 0.001$. The residual (within-people) mean square is 0.331 (df = 3948). The grand mean is 2.57.

4.3 Respondent's Demographic Profile

The study's sample comprised 291 respondents from Oman's fashion retail consumer base. The demographic composition includes respondents aged between 21 and 45. Educational levels range from preparatory to doctoral qualifications, while the demographic profile includes diverse shopping behaviors, familiarity with technology, and preferred fashion brand categories. Respondents represented diverse regions across Oman.

4.3.1 Age

Table 5: Age of Research Respondents, Frequency

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	21 – 25 years	99	34.0	34.1	34.1
	26 – 30 years	162	55.7	55.9	90.0

	31 – 35 years	18	6.2	6.2	96.2
	36 – 40 years	5	1.7	1.7	97.9
	41 – 45 years	6	2.1	2.1	100.0
	Total	290	99.7	100.0	
Missing	System	1	.3		
Total		291	100.0		

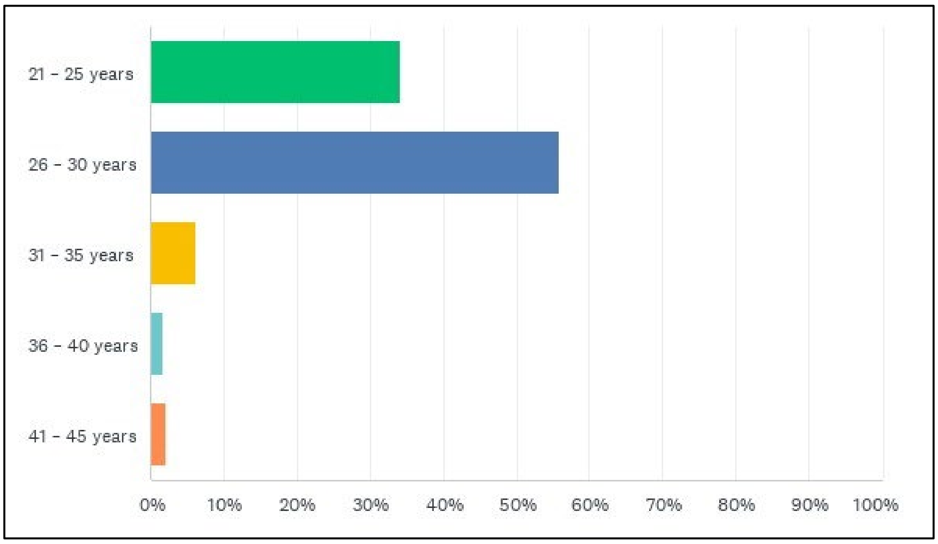

Figure 2: Age of Research Respondents

Based on Table 1 and the accompanying bar chart, the majority of respondents belong to younger age cohorts. The 26–30 years category constitutes the largest share, with 162 respondents (55.9 %). The 21–25 years group follows, with 99 respondents (34.1 %). Combined, these two age brackets account for about 90 % of the sample, demonstrating that the participant pool is heavily skewed toward young adults.

4.3.2 Educational Background

Table 6: Educational Background of the Research Respondents, Frequency

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Preparatory or less	2	.7	.7	.7
	Thanawiyah Amma / Secondary school	5	1.7	1.7	2.4
	Diploma / HND	14	4.8	4.9	7.3
	Bachelor's degree	213	73.2	74.5	81.8
	Master's degree	47	16.2	16.4	98.3

	Doctorate	5	1.7	1.7	100.0
	Total	286	98.3	100.0	
Missing	System	5	1.7		
Total		291	100.0		

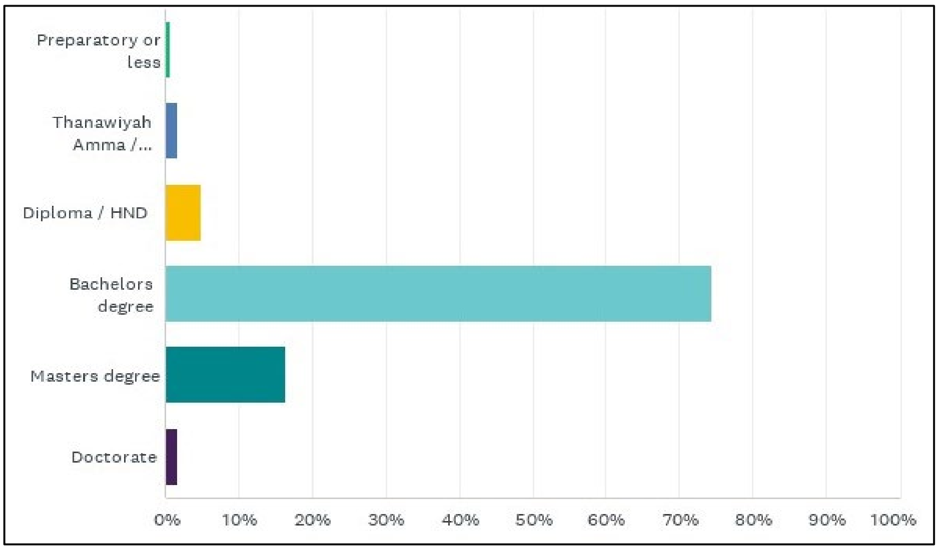

Figure 3: Educational Background of the Research Respondents

The sample in this study is predominantly composed of young, highly educated adults. Over half of the respondents (162, or 55.9%) fall in the 26-30 years age bracket, while another 34.1% (99 participants) are aged 21-25, together representing nearly 90% of the sample. In terms of education, a clear majority hold at least a bachelor's degree: 213 participants (74.5%) have bachelor's qualifications, 47 (16.4%) possess a master's degree, and 5 (1.7%) hold a doctorate. Consequently, more than 92% of the sample holds an educational level of bachelor's or higher, reflecting a highly educated and youthful respondent profile.

4.3.3 Shopping Persona

Table 7: Shopping Personal of Research Respondents, Frequency

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Fashion-focused regular shopper	6	2.1	2.1	2.1
	Occasional shopper	68	23.4	23.4	25.5

	Promotion-driven shopper	107	36.8	36.9	62.4
	Trend-influenced shopper	87	29.9	30.0	92.4
	Online shopper	22	7.6	7.6	100.0
	Total	290	99.7	100.0	
Missing	System	1	.3		
Total		291	100.0		

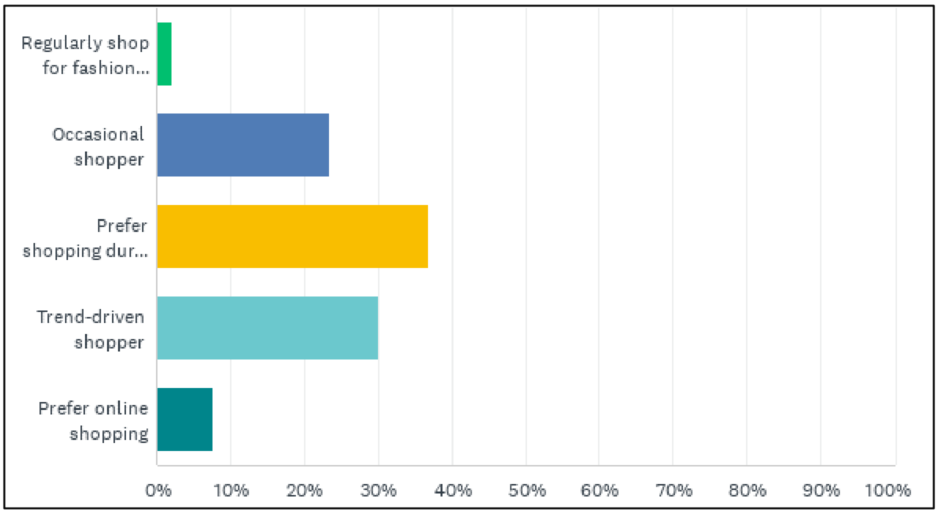

Figure 4: Shopping Personal of Research Respondents

The shopping personality profile of respondents shows a clear skew: 36.9% classify as Promotion-driven shoppers and 30.0% as Trend-influenced shoppers, meaning 66.9% of the sample is primarily motivated by discounts, sales, or the latest trends. The next largest segment is Occasional shoppers at 23.4%. Far fewer respondents are Fashion-focused regular shoppers (2.1%) or Online shoppers (7.6%). This distribution suggests that price sensitivity and trend alignment dominate over constant fashion orientation or purely online purchasing habits in your sample.

4.3.4 Technology Familiarity

Table 8: Technological Familiarity of the Research Respondents, Frequency

	Frequency	Percent	Valid Percent	Cumulative Percent

Valid	Actively adopts innovations first	23	7.9	7.9	7.9
	Extensively uses the latest technologies	90	30.9	31.0	39.0
	Basic skills and understanding	117	40.2	40.3	79.3
	Minimal usage	46	15.8	15.9	95.2
	Limited experience & comfort with technology	14	4.8	4.8	100.0
	Total	290	99.7	100.0	
Missing	System	1	.3		
Total		291	100.0		

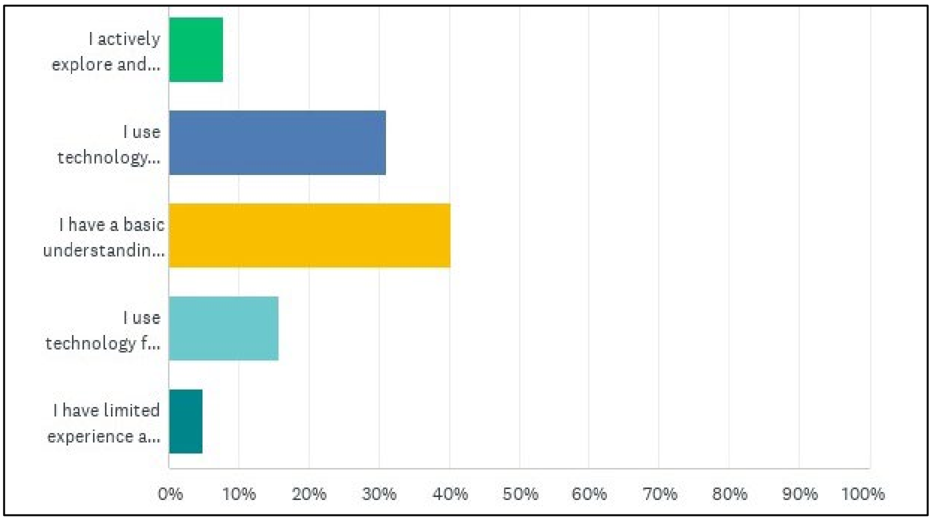

Figure 5: Technological Familiarity of the Research Respondents

Table 4 shows that most respondents possess at least a basic level of technological familiarity: 40.2% report "basic skills and understanding" and 30.9% "extensively use the latest technologies." Only 7.9% say they "actively adopt innovations first," while 15.8% have "minimal usage," and a small 4.8% feel they have "limited experience & comfort with technology." Thus, over 70% of the sample is moderately or highly tech-competent, suggesting good potential for AI tool adoption in Oman's fashion retail sector.

4.3.5 Brand Preference

Table 9: Brand Preference to Research Respondents, Frequency

	Frequency	Percent	Valid Percent	Cumulative Percent

Valid	Local independent brands	23	7.9	8.0	8.0
	International luxury labels	71	24.4	24.7	32.6
	Fast fashion / Retail chains	107	36.8	37.2	69.8
	Niche designers	68	23.4	23.6	93.4
	Online brands	19	6.5	6.6	100.0
	Total	288	99.0	100.0	
Missing	System	3	1.0		
Total		291	100.0		

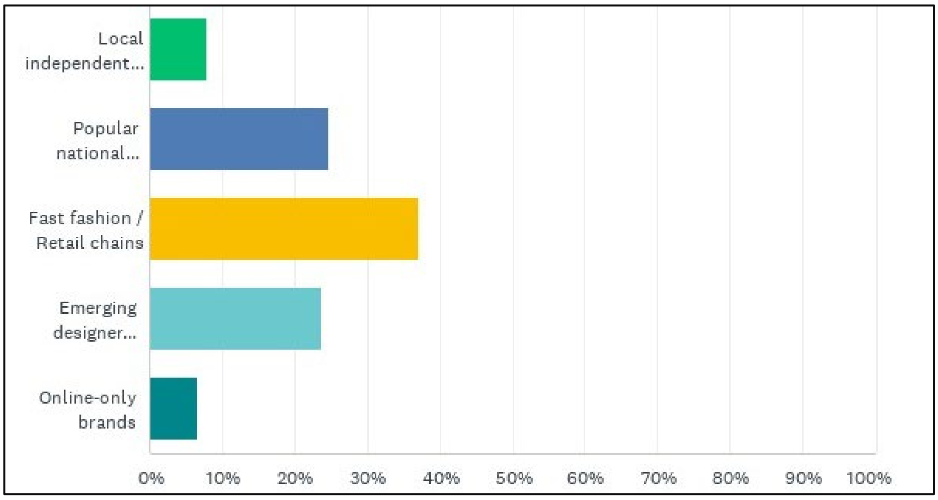

Figure 6: Brand Preference to Research Respondents

Fast fashion and retail chains dominate brand preference with 37.2% of respondents, followed by international luxury labels (24.7%) and niche designers (23.6%). Collectively, these categories account for over 85% of choices, highlighting consumers' strong attraction to both accessible mass-market options and premium designer labels, while local independent and online brands remain least favoured.

4.4 Descriptive Statistics

Table 10: Descriptive Statistics

IVs		Mean	Std. Deviation	Skewness	Kurtosis
PSB	PSB1	2.56	0.719	1.511	9.073
	PSB2	2.47	0.629	0.307	0.827
	PSB3	2.57	0.573	0.385	0.797

TDS	TDS1	2.47	0.66	0.808	3.064
	TDS2	2.59	0.611	0.24	3.175
	TDS3	2.6	0.616	0.252	1.311
OCT	OCT1	2.65	0.571	-0.376	0.681
	OCT2	2.57	0.58	-0.21	0.327
	OCT3	2.59	0.628	-0.264	0.441
TSA	TSA1	2.5	0.671	1.198	4.77
	TSA2	2.71	0.621	-0.239	1.233
	TSA3	2.54	0.605	0.082	0.882
BCE	BCE1	2.53	0.64	0.637	2.677
	BCE2	2.58	0.601	0.11	0.873
	BCE3	2.71	0.635	0.01	3.425
ECS	ECS1	2.63	0.654	0.494	3.083
	ECS2	2.67	0.672	0.997	5.831
	ECS3	2.71	0.581	-0.4	1.74
PD	PD1	2.71	0.536	-1.058	1.013
	PD2	2.66	0.584	-0.189	1.266
	PD3	2.51	0.595	0.029	0.254
PTB	PTB1	2.44	0.632	0.628	2.626
	PTB2	2.73	0.573	-0.369	4.176
	PTB3	2.67	0.649	0.292	4.224
PAR	PAR1	2.75	0.65	1.589	12.387
	PAR2	2.72	0.666	0.599	7.962
	PAR3	2.59	0.695	1.549	10.127

The descriptive statistics reveal moderate mean values across all variables, ranging between 2.44 and 2.75, with relatively low standard deviations, indicating consistent responses. Skewness values vary, suggesting slight asymmetry in data distribution, while kurtosis values range widely, showing differences in response concentration. Notably, PAR1 and PAR3 exhibit high skewness and kurtosis, indicating extreme clustering, whereas OCT items display more balanced distributions, reflecting overall variability in participants' perceptions across constructs.

Table 11: Mean Values of IVs Research

Descriptive Statistics							
	N	**Mean**	**SD**	**Skewness**		**Kurtosis**	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PSB	291	7.6014	1.24535	0.748	0.143	3.086	0.285
TDS	290	7.6483	1.33378	0.260	0.143	2.252	0.285

OCT	290	7.8103	1.23749	-0.440	0.143	2.277	0.285
TSA	289	7.7578	1.31636	0.096	0.143	2.471	0.286
BCE	287	7.8223	1.31151	-0.108	0.144	3.295	0.287
ECS	288	8.0069	1.35120	0.380	0.144	5.922	0.286
PD	291	7.8832	1.17448	-0.556	0.143	2.382	0.285
PTB	290	7.8483	1.23854	-0.633	0.143	1.958	0.285
PAR	290	8.0655	1.51550	2.075	0.143	20.602	0.285

The mean values of independent variables range between 7.60 and 8.07, indicating generally high responses. Standard deviations are relatively low, reflecting consistency in participant perceptions. Skewness values vary, with PSB and ECS showing positive skew, while OCT, PD, and PTB display negative skew. Kurtosis values are notably high for PAR and ECS, suggesting concentrated response patterns.

4.4.1 Factor Analysis

Exploratory Factor Analysis (EFA) was applied to identify underlying structures among nine independent variables related to consumer behavior in fashion retail. Data suitability was assessed using KMO and Bartlett's test, followed by factor extraction through principal component analysis. Varimax rotation enhanced interpretability, ensuring meaningful factor loadings. EFA provides an evidence-based foundation before confirmatory factor analysis validates the theoretical model.

4.4.2 Results of Exploratory Factor Analysis

The KMO measure of sampling adequacy is 0.850, which is well above the minimum acceptable threshold value of 0.5. This indicates that the sample and data are sufficient for conducting a factor analysis.

Table 12: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.850
Bartlett's Test of Sphericity	Approx. Chi-Square	503.088
	Df	36
	Sig.	.000

The KMO measure of sampling adequacy is 0.850, indicating excellent suitability for factor analysis. Bartlett's test of sphericity is significant ($\chi^2 = 503.088$, df = 36, $p < 0.001$), confirming that the data is appropriate for factor extraction.

Table 13:Factor Extraction using PrincipalComponent Analysis

Componen	Initial Eigenvalues			Extraction Sums of Squared			Rotation Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	3.350	37.218	37.218	3.350	37.218	37.218	1.012	11.245	11.245
2	0.960	10.671	47.889	0.960	10.671	47.889	1.012	11.242	22.487
3	0.914	10.161	58.049	0.914	10.161	58.049	1.008	11.205	33.692
4	0.859	9.547	67.596	0.859	9.547	67.596	1.006	11.179	44.870
5	0.764	8.485	76.081	0.764	8.485	76.081	1.005	11.168	56.038
6	0.601	6.675	82.756	0.601	6.675	82.756	1.003	11.142	67.180
7	0.573	6.362	89.118	0.573	6.362	89.118	0.994	11.040	78.220
8	0.521	5.790	94.908	0.521	5.790	94.908	0.983	10.924	89.144
9	0.458	5.092	100.000	0.458	5.092	100.000	0.977	10.856	100.000

The principal component analysis reveals that nine components explain 100% of the variance. The first component accounts for 37.22%, while subsequent components contribute progressively smaller shares. After rotation, each component explains approximately 10–11% of variance, indicating a more balanced distribution across factors. Cumulatively, the first six components account for 82.76%, suggesting that most of the data's variance can be captured by a reduced set of key factors.

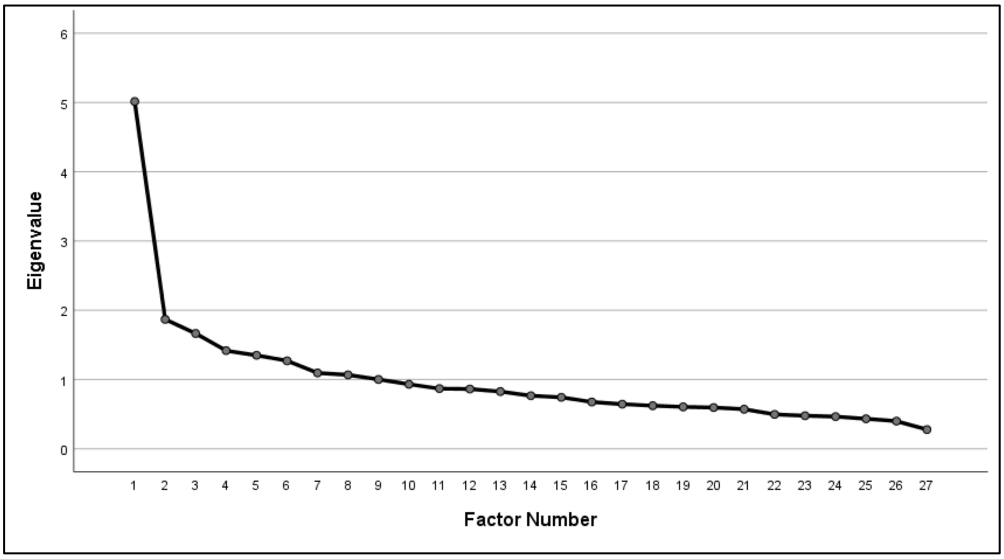

Figure 7: Scree Plot

The scree plot demonstrates a steep decline in eigenvalues from the first factor (≈5.0) to the second (≈2.0), then a gradual decrease. Applying the Kaiser criterion (eigenvalue >1.0), three factors are retained, as the "elbow" appears after the third factor, indicating the most meaningful underlying dimensions.

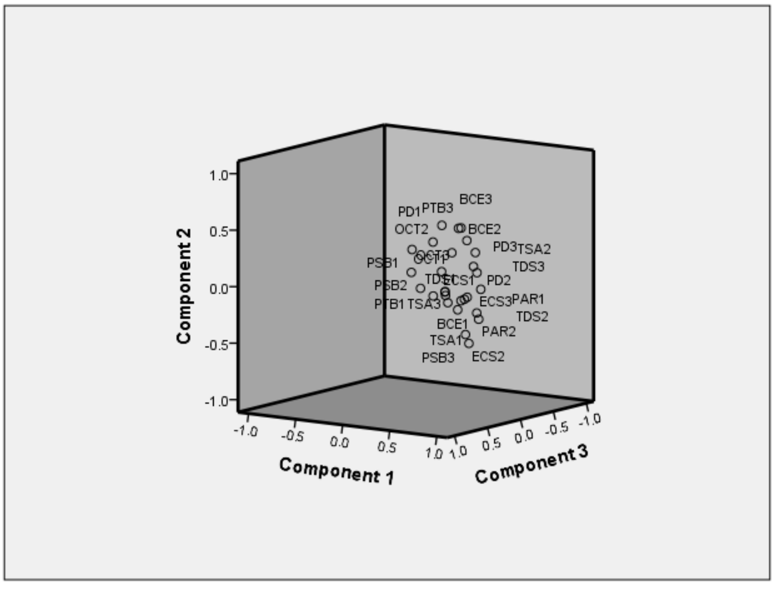

Figure 8: Component Plot in Rotated Space

The Component Plot in Rotated Space displays the final structure of the three extracted factors (components). The scatter of the variable markers (circles) suggests that while some variables cluster together along the axes, indicating factor grouping, the overall separation is somewhat intermingled.

Table 14: Communalities via Principal Component Analysis Extraction Method

	Initial	**Extraction**
PSB1	0.276	0.777
PSB2	0.179	0.992
PSB3	0.162	0.758
TDS1	0.304	0.999
TDS2	0.373	0.699
TDS3	0.295	0.999
OCT1	0.191	0.741
OCT2	0.255	0.999
OCT3	0.242	0.999
TSA1	0.312	0.870
TSA2	0.310	0.670
TSA3	0.187	1.000
BCE1	0.312	0.717
BCE2	0.223	1.000
BCE3	0.247	1.000
ECS1	0.325	1.000
ECS2	0.408	0.710
ECS3	0.262	1.000
PD1	0.239	0.691
PD2	0.298	1.000
PD3	0.213	1.000
PTB1	0.273	0.654
PTB2	0.286	0.653
PTB3	0.163	1.000
PAR1	0.468	0.740
PAR2	0.488	0.744
PAR3	0.288	0.938

The extraction communalities from PCA are generally high, with several values near 1.000 (e.g., TDS1, BCE3), showing that the three-component solution explains most variable variance. Even the lowest communalities, PTB2 (0.653) and PTB1 (0.654), exceed the 0.5 threshold, confirming that the retained factors effectively represent the original dataset and capture key underlying patterns.

Table 15: Rotated Component Matrix

	Component								
	1	2	3	4	5	6	7	8	9
PSB1	0.604								
PSB2	0.986								
PSB3	0.262								
TDS1		0.415							
TDS2		0.588							
TDS3		0.487							
OCT1			0.885						
OCT2			0.258						
OCT3			0.266						
TSA1				0.387					
TSA2				0.239					
TSA3				0.213					
BCE1					0.577				
BCE2					0.219				
BCE3					0.186				
ECS1						0.573			
ECS2						0.404			
ECS3						0.301			
PD1							0.515		
PD2							0.412		
PD3							0.388		
PTB1								0.598	
PTB2								0.494	
PTB3								0.293	
PAR1									0.582
PAR2									0.508
PAR3									0.324

The rotated component matrix reveals distinct loadings across variables, indicating a clear factor structure. PSB items predominantly load on Component 1, while TDS items load on Component 2. OCT variables align with Component 3, and TSA items load modestly on Component 4. BCE, ECS, PD, PTB, and PAR items show moderate to strong loadings on separate components, confirming the multidimensional representation of the constructs.

4.4.3 Mediation Analysis

This mediation analysis examines AI’s impact on consumer behavior in Oman’s fashion retail, with personalization-seeking and AR as mediators. It evaluates AI’s effects on mediators (Path a), mediators’ effects on outcomes (Path b), indirect effects, and overall total effects.

Path a: AI to Mediator

Table 16: Path a - AI to Mediators

Mediator	Coefficient	p-value	Significance
Personalization	0.1009	0.180	Not Significant
AR	0.3445	< 0.001	Significant

Path a analysis shows AI's effect on mediators, with a non-significant impact on Personalization ($\beta = 0.101$, $p = 0.180$) and a significant positive effect on AR ($\beta = 0.345$, $p < 0.001$), highlighting AR as a key AI-driven mediator.

Path b: Mediator to DV

Table 17: Path b - Mediators to Dependent Variables

Mediator	Dependent Variable	Coefficient	p-value	Significance
Personalization	Consumer Service	0.5	< 0.05	Significant
AR	Product Discovery	0.2637	< 0.001	Significant

Path b analysis indicates that both mediators significantly influence dependent variables: Personalization positively affects Consumer Service ($\beta = 0.500$, $p < 0.05$), and AR significantly impacts Product Discovery ($\beta = 0.264$, $p < 0.001$), confirming their key mediating roles.

Indirect Effects (Mediation)

Table 18: Indirect Effects (Mediation)

Mediator	Indirect Effect
Personalization	0.0234
AR	-0.0378

The mediation analysis of indirect effects shows that Personalization contributes a small positive effect (0.0234) on the relationship between AI and consumer outcomes, while AR exhibits a negative indirect effect (-0.0378). These results suggest that the mediating influence of AR and Personalization differs in direction and magnitude.

Total Effects

Table 19: Total Effects

Dependent Variable	Total Effect
Consumer Service	0.5142
Product Discovery	0.3067

The total effects analysis shows AI's overall impact, with a strong effect on Consumer Service (0.5142) and a moderate effect on Product Discovery (0.3067), reflecting combined direct and indirect influences.

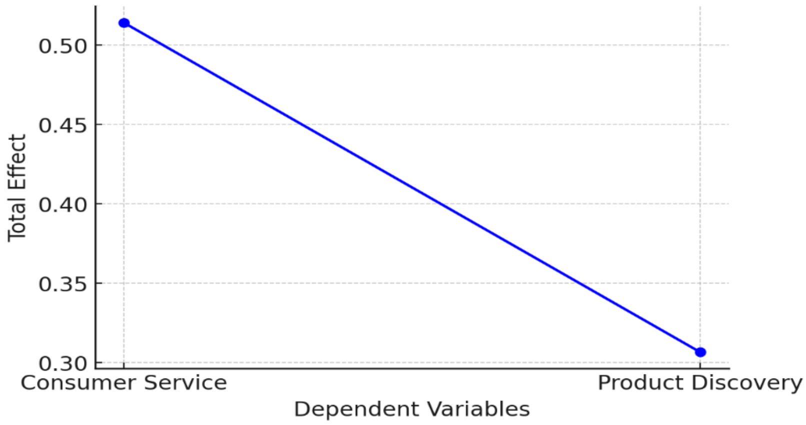

Figure 9: Total effects of AI on consumer service and product discovery

Figure 9 shows AI's total effects on dependent variables, with a stronger impact on Consumer Service (≈0.51) and a weaker effect on Product Discovery (≈0.31), indicating AI more effectively enhances consumer service than facilitates product discovery.

4.5 PearsonCorrelation Analysis

Table 20: Pearson Correlation Coefficient under Consumer Behavior

	PSB	TDS	BCE	OCT	TSA
PSB	1	.147** to .184**	.126*	.015 to .262**	.118*
TDS	.147** to .184**	1	.186** to .251**	.100 to .266**	.226**
OCT	.126*	.186** to .251**	1	.129* to .175**	.187**
TSA	.015 to .262**	.100 to .266**	.129* to .175**	1	.264**
BCE	.118*	.226**	.187**	.264**	1

The Pearson correlation analysis under Consumer Behavior shows positive relationships among all variables. PSB, TDS, OCT, TSA, and BCE exhibit weak to moderate correlations, with significance levels ranging from *p*< 0.05 to p< 0.01, indicating interrelated dimensions of consumer behavior in the studied context.

Table 21: Pearson Correlation Coefficient under Consumer Shopping Patterns

	ECS	PD	PTB	PAR
ECS	1	0.107, 0.201**, 0.186**	0.186**, 0.228**, 0.100	0.305**, 0.195**, 0.180**
PD	0.107, 0.201**, 0.186**	1	-0.043, 0.076, 0.217**	0.140*, 0.285**, -0.025
PTB	0.186**, 0.228**, 0.100	-0.043, 0.076, 0.217**	1	0.255**, 0.228**, 0.144*
PAR	0.305**, 0.195**, 0.180**	0.140*, 0.285**, -0.025	0.255**, 0.228**, 0.144*	1

The Pearson correlation analysis for Consumer Shopping Patterns indicates positive associations among ECS, PD, PTB, and PAR, with correlations ranging from weak to moderate. Several relationships are significant at *p*< 0.05 or p < 0.01, highlighting interconnected shopping behaviors and patterns in the fashion retail context.

4.6 Hypothesis Testing Using Mean Values

4.6.1 Testing Hypothesis Using Two-Way ANOVA

Table 22: Test of Homogeneity of Variance

	Levene's Statistic	**df1**	**df2**	**Sig.**
PSB	3.211	3	267	0.024
TDS	0.733	3	267	0.533
OCT	0.241	3	267	0.868
TSA	0.073	3	265	0.975
BCE	1.977*	3	262	0.118
ECS	0.108*	3	263	0.956
PD	0.274*	2	267	0.760
PTB	0.588*	2	266	0.556
PAR	0.197*	3	265	0.899

The Levene's test for homogeneity of variance shows that most variables, including TDS, OCT, TSA, BCE, ECS, PD, PTB, and PAR, meet the assumption of equal variances (p > 0.05).

Only PSB violates this assumption (p = 0.024), indicating potential variance differences across groups.

Table 23: Two-Way ANOVA of IVs

		Sum of Squares	df	Mean Square	F	Sig.
PSB	Between Groups	.700	3	.233	.634	.594
	Within Groups	98.274	267	.368		
	Total	98.974	270			
TDS	Between Groups	1.230	3	.410	1.120	.341
	Within Groups	97.744	267	.366		
	Total	98.974	270			
OCT	Between Groups	.224	3	.075	.202	.895
	Within Groups	98.750	267	.370		
	Total	98.974	270			
TSA	Between Groups	.228	3	.076	.209	.890
	Within Groups	96.129	265	.363		
	Total	96.357	268			
BCE	Between Groups	1.404	4	351	.952	.435
	Within Groups	96.663	262	.369		
	Total	98.067	266			
ECS	Between Groups	.512	4	.128	.344	.848
	Within Groups	97.857	263	.372		
	Total	98.369	267			
PD	Between Groups	.240	3	.080	.216	.885
	Within Groups	98.734	267	.370		
	Total	98.974	270			
PTB	Between Groups	.276	3	.092	.249	.862
	Within Groups	98.498	266	.370		
	Total	98.774	269			

PAR	Between Groups	1.902	4	.476	1.302	.270
	Within Groups	96.765	265	.365		
	Total	98.667	269			

The two-way ANOVA results indicate no significant differences between groups for all independent variables. PSB, TDS, OCT, TSA, BCE, ECS, PD, PTB, and PAR show p-values greater than 0.05, suggesting that group membership does not significantly influence these variables, and the within-group variability largely accounts for the observed data variation.

4.6.2 Consumer Behavior Mediation Analysis Using AMOS.

Table 24: Mediation Analysis Results of Consumer Behavior

	IV	**A Path**	**B Path**	**Direct Effect**	**Indirect Effect**
CBMed_C	PSB_Cat	.3377**	-0.0663	0.0105	-0.0224
	TDS_Cat	.4922**	-0.1692	0.1843*	-0.0833
	OCT_Cat	.4308**	-0.0641	0.0040	-0.0276
	TSA_Cat	0.3727**	-0.0465	-0.0365	-0.0173
	BCE_Cat	0.3943**	-0.0225	-0.0845	-0.0089
*p < 0.05, **p < 0.01					

Table 20 shows that consumer behavior partially mediates relationships between certain independent variables (IVs) and outcomes. For technology-driven solutions (TDS_Cat), the indirect effect is significant (−0.0833, $p < 0.05$), while the direct effect remains positive (0.1843, $p < 0.05$). Other IVs (PSB_Cat, OCT_Cat, TSA_Cat, BCE_Cat) show non-significant indirect effects, suggesting limited mediating roles of consumer behavior for those paths

4.6.2.1 SEM of Consumer Behaviour

Table 0-25: SME Results for Consumer Behavior

Variable	Mean Value	Path Coefficient from CBMed	Error Term (e)
PSB	2.52	1.00	0.12
TDS	2.54	1.60	0.11
OCT	2.61	1.43	0.11
TSA	2.58	1.36	0.13
BCE	2.60	1.58	0.12

Table 21 reports that among the predictors of consumer behavior (CBMed), TDS (technology-driven solutions) shows the highest path coefficient of 1.60 (mean = 2.54, error = 0.11), followed by BCE at 1.58 (mean = 2.60, error = 0.12). OCT (1.43) and TSA (1.36) also have strong effects, while PSB is baseline (1.00, mean 2.52).

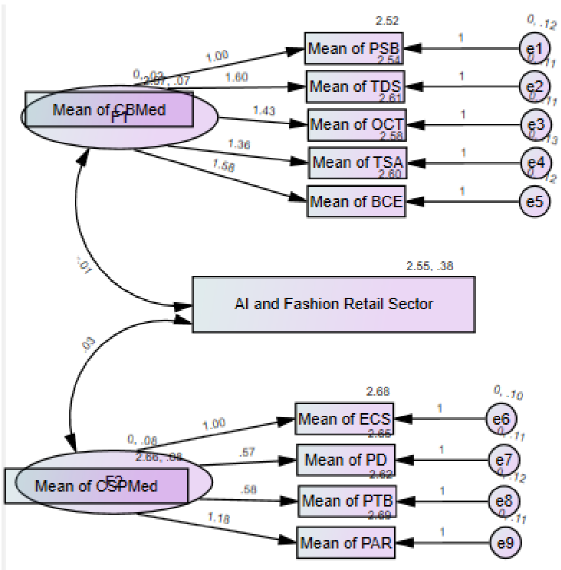

Figure 10: Structural Equation Model of AI Integration in the Fashion Retail Sector

Figure 10 shows that the latent mediator Consumer Behavior (CBMed) has strong positive paths from independent variables such as Technology-Driven Solutions (TDS; β ≈ 1.60), Budget Consciousness / BCE (≈ 1.58), Omnichannel Technology (OCT; ≈ 1.43), and Tech-Savviness Attitude (TSA; ≈ 1.36), with Personalization-Seeking Behavior (PSB) as baseline (1.00). These IVs collectively influence CBMed, which in turn has a positive effect on the outcome variable (AI and Fashion Retail Sector), indicating mediation. The path coefficients suggest that TDS and BCE are the strongest drivers of consumer behavior in this model.

4.6.2.2 Consumer Shopping Patterns Mediation Analysis Using AMOS.

Table 26: Mediating Analysis Results of Consumer Shopping Patterns

	IV	A Path	B Path	Direct Effect	Indirect Effect
CSPMed_C	ECS_Cat	0.4569**	0.1021	0.0174	0.0467
	PD_Cat	0.3941**	0.1338	-0.0442	0.0527
	PTB_Cat	0.4309**	0.1244	-0.0226	0.0536
	PAR_Cat	0.4579**	0.0761	0.0558	0.0349
*p < 0.05, **p < 0.01					

Table 22 shows that consumer shopping patterns (CSPMed_C) significantly mediate several relationships. All A paths (ECS, PD, PTB, PAR) are significant at $p < 0.01$, indicating strong links from independent variables to CSPMed. Indirect effects are positive for ECS (0.0467), PD (0.0527), PTB (0.0536), and PAR (0.0349). Some direct effects are negative (PD, PTB), suggesting partial mediation.

4.6.2.3 SEM of Consumer Shopping Patterns

Table 27: SEM Results for Consumer Shopping Patterns

Variable	Mean Value	Path Coefficient from CBMed	Error Term (e)
ECS	2.68	1.00	0.10
PD	2.65	0.57	0.11
PTB	2.62	0.58	0.12
PAR	2.69	1.18	0.11

Table 23 presents the SEM results for the Consumer Shopping Patterns (CSPMed) model. Among the predictors, PAR (Personalized Augmented Reality) exhibits the largest path coefficient (1.18, mean = 2.69, error = 0.11), indicating a strong influence. PD (Product Discovery) and PTB (Phygital & Touchpoint Beacons) show moderate effects (0.57 and 0.58, respectively). ECS (Enhanced Consumer Service) serves as the baseline (1.00, mean = 2.68, error = 0.10). These results suggest that AR personalization plays a particularly significant role in shaping consumer shopping behavior under the AI-driven retail paradigm.

4.7 Summary of Key Findings

Chapter 4, based on the analysis of 291 consumer responses in Oman's Fashion Retail Sector, provides key insights into AI's influence, driven by a sample largely consisting of young, highly educated, and tech-engaged consumers. The primary purchase drivers for this group are price sensitivity (Promotion-driven) and following the latest trends (Trend-influenced), with a strong preference for fast fashion chains. The main finding from the total effects analysis is that AI's influence is significantly stronger on Enhanced Consumer Service (0.5142) than on Product Discovery (0.3067), indicating its current primary role is improving the service experience. Furthermore, the mediation analysis confirmed that all key drivers of consumer shopping patterns including Enhanced Service, Product Discovery, Phygital/Beacons, and Augmented Reality have strong, positive, and statistically significant relationships with the overall dependent variable, underscoring their collective critical role in the successful integration of AI technologies within the sector.

CHAPTER 5: CONCLUSION

The study concludes that the integration of Artificial Intelligence (AI) serves as a transformative and significantly positive force in shaping consumer behavior and shopping patterns within Oman's Fashion Retail Sector (FRS). The empirical evidence confirmed that all key technological drivers specifically ECS, Product Discovery, Phygital/Touchpoint Beacons, and AR exhibit strong, significant positive links to consumer outcomes, with AI's overall effect being most potent in improving customer service delivery. This validation, drawn from a sample of highly educated, youthful, and predominantly Promotion-driven (budget-conscious) and Trend-influenced consumers, underscores the high receptivity of the Omani market to AI-driven retail experiences. Based on these findings, the study offers key recommendations for fashion retailers in Oman: first, investments must be prioritized in AI tools that facilitate Enhanced Consumer Service (e.g., 24/7 personalized chatbots) and optimize the efficiency of Product Discovery (advanced recommendation engines). Second, retailers should aggressively pursue an omnichannel/Phygital strategy that seamlessly integrates in-store experiences with digital tools like AR try-ons and touchpoint beacons to create immersive, low-friction shopping journeys. Finally, given the sample's high budget-consciousness, AI should be leveraged to provide dynamic pricing, personalized offers, and cost-effective alternatives to build loyalty among price-sensitive consumers. Despite the robust findings, the research acknowledges limitations, primarily stemming from its cross-sectional research design, which captures consumer attitudes at only a single point in time and limits the assessment of long-term changes. Furthermore, the study relied on self-reported data (a structured online survey), introducing potential respondent bias. The focused population of consumers in Oman's FRS also restricts the generalizability of the results to other regions, retail sectors, or broader age demographics.

Considering these limitations, the future implications for research are clear: subsequent studies should adopt a longitudinal approach to track the evolution of AI's impact over time and may incorporate a broader, geographically diverse sample to enhance external validity. There is also a compelling need for future work to integrate objective measures (like actual sales data or loyalty metrics) alongside self-reports and to specifically investigate the unique challenges of cultural influences and consumer privacy concerns related to AI in the Middle East.

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