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Beyond the algorithm: How artificial intelligence-driven consumer insights shape young consumers' purchasing behavior in the age of privacy paradox

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Abstract

This study examines the impact of artificial intelligence (AI)-driven consumer insights on the purchasing behavior of young consumers, with a focus on the mediating role of perceived personalization and the moderating effect of privacy concerns. Grounded in the Technology Acceptance Model and privacy calculus theory, the study adopts a quantitative research design. Survey data were collected from 376 consumers in the Middle East, and the hypotheses were tested using structural equation modeling. The findings reveal that AI-driven consumer insights significantly enhance purchasing behavior through perceived personalization. However, high levels of privacy concern diminish this effect, indicating a conditional relationship. The research highlights the dual role of personalization and privacy in shaping consumer responses to AI-driven marketing, offering new theoretical insights into digital consumer behavior. Marketers and AI developers should strike a balance between personalization efforts and transparent privacy practices to maintain consumer trust and engagement in AI-powered environments.

Keywords: AI-driven consumer insights, Middle East, Perceived personalization, Privacy concerns, Purchasing behavior.

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Institutional Review Board Statement: This research was conducted in strict compliance with the 1964 Helsinki Declaration and its subsequent amendments, as well as the guidelines of the researcher's institution. This research was not a medical study, nor did it involve human experimentation as contained in the Declaration of Helsinki. All respondents in the study were over 18 years of age and voluntarily completed the research questionnaire. The information provided by the respondents was strictly used for this study and treated with utmost confidentiality and anonymity.
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1. Introduction

Predictive analytics has become a crucial tool for understanding and forecasting market trends, giving companies a substantial competitive advantage as they navigate the complexities of customer behavior [1]. Consumer behavior and experience are crucial in determining the success of businesses across various industries in today's digitally dynamic environment. The introduction of Artificial Intelligence (AI) has significantly transformed how businesses understand, assess, and respond to their customers' needs by leveraging sophisticated algorithms, machine learning, and data analytics [2]. Predictive analytics is greatly improved by AI, which introduces cutting-edge technologies that can handle and analyze data more efficiently [1]. AI has become a disruptive force in digital marketing due to its unmatched capacity to replicate human behavior, analyze large datasets, and enhance decision-making [3, 4].

AI-driven solutions in marketing have proven crucial in forecasting campaign results, refining message tactics, and generating consumer data that let companies adjust their products to meet changing consumer demands [5]. Nowadays, AI tools identify sustainable products, for example, Google's Eco-Friendly Labels.

According to the Technology Acceptance Model (TAM), perceived usefulness and perceived ease of use significantly impact users' acceptance of technology [6]. Therefore, AI-driven consumer Insights are deemed beneficial when they offer tailored experiences that suit the tastes of young customers. AI's perceived usefulness and perceived ease of use, as well as attitudes toward technology, have a significant and positive influence on the intention to make an impulsive purchase [7].

Future research is needed to examine AI capabilities in detail, the dynamics of consumer decision-making over time, and the contextual elements that influence customer responses [8, 9] calls for future studies to understand AI's impact on consumer behavior by examining the dynamics of relationships across various consumer demographics and industry contexts. Joseph, et al. [10] Call for future research in consumer insights and cross-device personalization, which allows businesses to maintain customized marketing strategies while preserving user privacy. Moreover, [11]. Encourage future researchers to investigate how consumer trust influences the adoption of personalized marketing strategies, particularly in countries with varying degrees of technological adoption and data literacy. Advancements in AI technologies will shape predictive analytics' future, better data integration and quality; therefore, addressing ethical and privacy issues is a future research direction [1].

The rapid integration of AI-driven consumer Insights into marketing plans has changed how companies interact with Gen Z and Millennials, two generations of digital natives with unique buying habits. Although AI enables predictive targeting and hyper-personalization, this relationship is complicated by rising privacy concerns and the mediating effect of perceived personalization. Few studies have examined how young customers react to AI-driven insights, especially in situations where privacy and personalization intersect, despite earlier research highlighting AI's role in marketing. This study bridges this gap by combining the TAM [6] and privacy calculus theory [12]. Most research examines AI's influence on customer behavior separately; TAM emphasizes perceived usefulness but ignores privacy issues. Furthermore, data-sharing trade-offs are explained by Privacy Calculus Theory, but the role of AI in personalization is neglected.

In this study, perceived personalization serves as a mediator that converts the benefits of AI-driven consumer insights into observable results, including an increase in purchase behavior. Nevertheless, it is crucial to emphasize that using AI ethically to understand and influence customer behavior is essential [2]. Retaining integrity and trust requires the implementation of ethical AI, protection of customer privacy, and transparency in data usage. Therefore, this study proposes that privacy concerns moderate the relationship between AI-driven consumer insights and PP. AI-Driven Consumer Insights may be seen as less helpful by young consumers who have serious privacy concerns, which would lessen the impact of personalization.

To explain why some young consumers accept AI-driven personalization while others reject it because of privacy concerns, and how perceived personalization serves as a psychological link between AI insights and purchase decisions. The current study provides a comprehensive framework for understanding how consumer insights driven by AI influence the purchasing decisions of young customers in the Middle East. The model offers valuable insights for researchers and practitioners seeking to leverage AI technology to effectively engage young customers, considering perceived personalization as a mediator and privacy concerns as a moderator. The model also emphasizes the importance of addressing privacy issues to maximize the benefits of AI-driven personalization. According to the observed gaps in the literature, the following research questions have been developed for this study:

RQ1. How does AI-Driven Consumer Insights influence young consumers' purchasing behavior?

RQ2. What role does perceived personalization play in mediating the relationship between AI-driven insights and young consumers' purchasing behavior?

RQ3. How do privacy concerns moderate the effectiveness of AI-driven consumer insights in shaping perceived personalization?

There are five more sections in the present study. Section 2 presents a comprehensive literature review. Thereafter, the methodological procedures used to conduct the study are described in Section 3. Subsequently, findings are presented in Section 4. Theoretical and practical implications are discussed in Section 5. The last section presents conclusions, limitations, and future research directions.

2 Literature Review

2.1. Purchasing Behavior

With the development of AI technology and its applications, consumer behavior has undergone significant changes. AI tools emerge as practical tools in creating consumer engagement due to their capacity to deliver valuable data on many elements that influence customer behavioral intents [13]. It is crucial to comprehend how consumers' interactions with these applications across various platforms and touchpoints influence their behavior and its components, including personality, attitude, engagement, decision-making, and trust. AI identifies similarities in prior interactions and behaviors that traditional analysis might overlook, enabling companies to anticipate future demands and tailor their offerings accordingly. AI-driven insights would allow organizations to optimize their tactics for optimal impact, whether it is through the prediction of purchase patterns, comprehension of browsing activities, or the identification of sentiment through social media interactions [2].

AI-driven personalization has had a profound impact on consumer behavior in the e-commerce sector, significantly altering the online shopping experience and influencing future market trends [14]. Organizations can effectively analyze and forecast purchasing intentions with the help of AI-driven customer data [7]. When young customers make purchases, their decision-making process, purchasing frequency, and brand loyalty are all considered aspects of their purchasing behavior.

AI optimizes marketing efforts and boosts conversion rates by helping firms anticipate and respond to changes in consumer behavior in real-time [15]. Businesses must be able to accurately predict customer behavior to succeed in today's competitive marketplace. Enterprises are increasingly utilizing AI-driven solutions to gain valuable insights into customer preferences and purchasing patterns due to the rapid advancements in AI technologies [16]. Customized product recommendations are one of the main ways AI-driven personalization influences customer behavior [14, 17]. Claim that using AI-selected ads can increase conversion rates by 200% to 300% only by adding another point of contact with a customer.

2.2. AI-Driven Consumer Insights

In terms of marketing science, by forecasting customer behavior, marketers have seen the advantages of AI. AI-driven consumer insights present firms with a wealth of opportunities to better understand and engage their target market [3]. It helps organizations better understand their target audiences by utilizing AI technologies to analyze massive datasets and uncover insightful information about customer behavior, preferences, and trends [18]. Moreover, it helps firms better understand customer preferences and create a marketing funnel that appeals to a specific demographic [17].

Businesses can provide young consumers with highly personalized experiences, including customized product recommendations, targeted ads, and content, thanks to AI-driven insights. This strengthens the perception among young customers that the company recognizes and meets their unique demands. Rosário and Dias [3] Examine the possibilities and challenges of integrating AI-driven consumer insights into corporate operations, as well as how businesses can overcome barriers such as data privacy concerns, bias, and integration issues to fully leverage these opportunities. To create individualized recommendations, targeted ads, and customized experiences, the data of young consumers is analyzed using AI technologies, such as machine learning, natural language processing, and recommender systems.
The following hypothesis was developed in consideration of these arguments.

H_1: AI-Driven Consumer Insights have a positive impact on Young Consumers' Purchasing Behavior.

2.3. Perceived Personalization

The degree to which young consumers believe that the goods, services, or advertising they are exposed to is customized to meet their unique requirements and preferences is known as perceived personalization. By providing relevant and personalized experiences, AI-driven consumer insights enhance perceived personalization. AI has completely transformed marketing strategies by enabling companies to provide highly customized experiences through real-time interaction, generative AI, and predictive modeling [10].

According to TAM, perceived usefulness and perceived ease of use are two significant factors that affect users' acceptance and adoption of technology. Perceived personalization can be viewed as an expression of perceived usefulness in the context of AI-driven consumer insights, where customers perceive AI-driven insights as beneficial when they result in tailored experiences. Babu demonstrated how AI-driven tools, such as recommender systems and predictive analytics, enhance customer satisfaction by providing tailored recommendations. They emphasize the importance of perceived ease of use in improving the efficacy of AI-driven personalization [10].

When Kumar, et al. [19] Investigated the use of AI in personalized engagement marketing. They discovered that by providing customized experiences, AI-driven insights significantly improve consumer engagement. This study lends support to the concept that the relationship between AI-driven insights and customer behavior is mediated by perceived personalization. Young consumers are more likely to engage in positive purchasing behaviors, including making repeat purchases, spending more money, and displaying brand loyalty, when they believe that a company provides individualized experiences.

The impact of AI-driven personalization on customer engagement and trust was investigated by Baldauf, et al. [20]. They discovered that customers and companies have greater emotional bonds when they have personalized experiences, which supports the concept that perceived personalization acts as a mediator. AI-driven personalization has effects that extend beyond short-term revenue; it also impacts enduring relationships with consumers. Businesses can foster brand loyalty and promote repeat business by making the purchasing experience more engaging and personalized [14]. According to Kumar, et al. [19], providing customized offers and recommendations through AI-driven personalization significantly enhances purchase behavior. It dramatically boosts purchase intentions. The following hypothesis was developed in consideration of these arguments. [9, 21, 22].

H_2: Perceived Personalization mediates the relationship between AI-driven consumer insights and Young Consumers' Purchasing Behavior.

2.4. Privacy Concerns

The level of concern among young consumers about how businesses gather, store, and use their personal data is referred to as privacy concerns. Concerns about the use of personal information and the potential consequences of misuse have grown among people globally. These concerns have sparked an increasing discussion about how to strike a balance between protecting consumer privacy and the benefits of personalization [23].

Consumer perceptions of privacy play a vital role in determining their readiness to provide information while dealing with websites or online platforms [24]. Although case studies from Netflix, Amazon, and Google demonstrate their utility in real-world situations, issues with data privacy, algorithmic biases, user acceptance, and talent recruitment persist [2]. A recent global study by Kumari and Thakur [25] supports this concern, emphasizing that while AI significantly improves purchasing behavior through data-driven personalization, it also presents ethical dilemmas such as algorithmic bias and data privacy, which must be addressed to preserve consumer trust [25].

Using AI-Driven Consumer Insights presents substantial privacy challenges because of the enormous collection and analysis of consumer data, which raises concerns about the handling and use of personal information [1, 26]. Concerns regarding data security, transparency, and the handling of personal information are raised by extensive data collection [8, 26, 27]. Ahamed [28] further illustrates how AI-powered tools in Middle Eastern retail have advanced personalization and efficiency but warns that these systems rely on deep data integration, amplifying consumer anxieties over privacy and control of personal information [28].

Ethical issues, including privacy, algorithmic bias, and consumer autonomy, must continue to be crucial as AI personalization grows more sophisticated to guarantee responsible deployment and sustained customer trust [10]. The results of a study by Nath [9] indicate that building consumer trust, which in turn influences purchase decisions, requires increased awareness of AI personalization, privacy, and ethical concerns, as well as satisfaction and overall experience.

While segment identification customizes strategies, automation saves time and money. Nonetheless, issues with integration, bias reduction, and privacy must be addressed [3]. The efficacy of AI-driven consumer insights may be hindered by concerns about privacy. The influence of AI-driven consumer insights on perceived personalization and purchase behavior may be lessened for young consumers who are particularly concerned about their privacy, as they are less likely to value or trust individualized experiences.

Privacy issues have arisen among AI technology adopters because of the technology's extensive integration. Privacy issues have significantly impacted consumer trust in AI systems. The privacy calculus theory can be used to understand better the elements influencing consumer trust in AI recommendation systems [23]. Particularly in the context of a digital environment, this theory helps explain why consumers have varying levels of willingness to reveal personal information.

Teepapal [24] develops and analyzes a comprehensive S-O-R model that connects AI stimuli to customer perceptions of usefulness, privacy concerns, and trust, ultimately leading to consumer engagement. According to TAM, technology adoption is influenced by its perceived usefulness and ease of use [6]. However, when consumers are concerned about the privacy of their data, the perceived value of AI-driven insights (such as personalization) may decrease. The moderating influence of privacy concerns may weaken the relationship between AI-driven consumer insights and perceived personalization.

Although AI-enabled personalization in interactive marketing has the potential to be beneficial, it also poses a risk of adverse effects if it limits options or compromises people's privacy Teepapal [24]. Sipos [29] found that privacy concerns stand out as a significant moderating factor that may impede the positive effect of personalization on trust and consequent purchasing behaviors. Similarly, Shoukat, et al. [30] concluded that privacy concerns have a substantial impact on perceived usefulness. Additionally, perceived usefulness acted as a mediator in the relationship between privacy concerns and behavioral intentions.

$H_{3:}$ Privacy Concerns moderate the relationship between AI-driven consumer insights and Perceived Personalization, such that the relationship is weaker when privacy concerns are high.

The purpose of the proposed research model is to investigate how AI-driven consumer insights influence the purchasing decisions of young customers, while considering the moderating effect of privacy concerns and the mediating role of perceived personalization (Figure 1). The model is based on the TAM, which describes how user acceptance of technology is influenced by its perceived usefulness and ease of use.

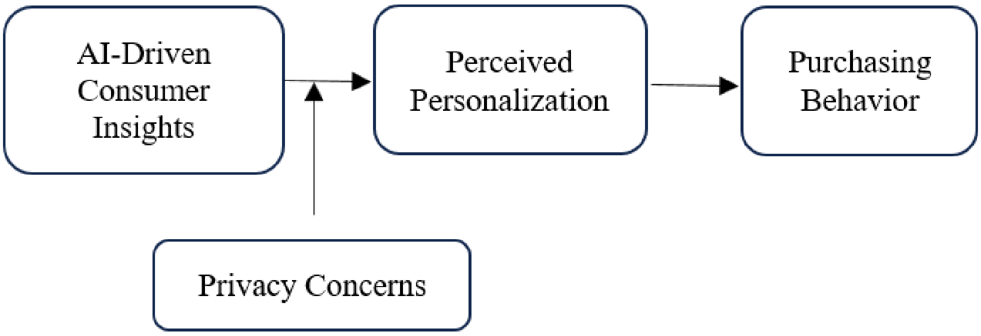

Figure 1.
Research Model.

3. Methodology

This study is quantitative in nature and employs a positivist paradigm and deductive research methodology. Numerous previously validated items from literature (i.e., Babu, et al. [16]; Bhagat, et al. [21]; Cheng and Jiang [27]; Dai and Liu [22]; Kumar, et al. [31]; Dai and Liu [22]; Nath [9]; Rosário and Dias [3], Teepapal [24]) served as the foundation for the measuring instrument. Academic and industry research on the relationship between AI and consumer behavior, particularly among young people, has increased. Learning how AI influences their purchasing decisions is particularly relevant to young people [32]. Research on AI is particularly well-suited to the Middle East because of its rapidly growing digital economy, extensive social media use, and distinctive cultural norms. Consequently, the study focuses on Middle Eastern young consumers.

The data was analyzed using SmartPLS 4.0.5.9. Due to its ability to handle complex models with several constructs, PLS-SEM was used in this investigation [33]. The software's user-friendly interface and improvements in modeling latent components using PLS-SEM and covariance-based structural equation modeling (CB-SEM) methodologies have made it increasingly popular [34]. A two-step analytical approach was employed, beginning with the assessment of the measurement model to establish reliability and validity. This step involved evaluating indicator loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE), in addition to Confirmatory Tetrad Analysis (CTA) to confirm the reflective nature of the multi-item constructs [35]. Discriminant validity was established through the Heterotrait-Monotrait (HTMT) ratio criterion [36].

To address multicollinearity, the Variance Inflation Factor (VIF) values were examined and found to be below the acceptable threshold, indicating no collinearity issues. Standard method variance (CMV) was tested using the complete collinearity approach, with findings showing no significant bias [37]. Following this, the structural model was evaluated in terms of explanatory power (R^2), predictive relevance (Q^2), and predictive accuracy (RMSE) [38]. Additional robustness checks, including assessments for non-linearity, endogeneity, and unobserved heterogeneity, confirmed the model's stability and validity [39].

Standard method variance (CMV) was assessed using the full collinearity test as recommended by Kock [37]. All variance inflation factor (VIF) values were below the threshold of 3.3, indicating that CMV [40] is not a concern in this study. These results confirm that the model is free from substantial standard method bias and that the constructs are measured distinctly.

The study included a total of 376 participants, with a slight majority identifying as male (54.3%, n = 204) compared to female (45.7%, n = 172). The sample predominantly comprised young consumers, with the largest age group being 18–22 years (37.5%, n = 141), followed by 23–26 years (30.3%, n = 114), 27–30 years (16.5%, n = 62), and 31–34 years (15.7%, n = 59). Education levels were highly skewed toward higher education: 50.3% (n = 189) held a bachelor's degree, and 49.7% (n = 187) had a graduate degree, with no representation from secondary school or diploma holders.

4. Findings and Discussion

The descriptive statistics for all constructs (measured on a 5-point scale) indicate generally positive perceptions of AI-driven insights, personalization, and purchasing behavior, alongside moderate to high privacy concerns. For AI-Driven Consumer Insights, all items (AI1–AI5) showed high mean scores (range: 4.31–4.50, SD = 0.64–0.71), reflecting strong agreement that AI tools enhance consumer insights. Perceived Personalization items (PP1–PP6) also scored favorably (means: 4.02–4.37, SD = 0.68–0.82), with PP5 (Mean = 4.37, SD = 0.68) indicating the strongest consensus on personalized experiences.

Table 1.
Descriptive Statistics.

	Mean	SD
AI1. I believe AI helps brands predict my preferences and show me ads that match my interests	4.4548	0.71036
AI2. I feel that AI-driven insights allow brands to offer me products and services that are tailored to my needs	4.5027	0.64498
AI3. AI helps brands understand my shopping journey and provide relevant recommendations at each stage	4.4548	0.65571
AI4. I notice that brands use AI to adapt their strategies based on my behavior and feedback quickly	4.4122	0.68722
AI5. I trust brands more when they use AI responsibly and are transparent about how they use my data	4.3112	0.66652
PP1. The product recommendations I receive feel like they are specifically designed for me	4.2234	0.77500
PP2. I find the ads and offers I receive to be highly relevant to my interests	4.3511	0.70363
PP3. The content I see online (e.g., social media, websites) is tailored to my preferences	4.3218	0.75553
PP4. I appreciate it when brands allow me to customize products or services to suit my preferences	4.3351	0.70763
PP5. The emails and messages I receive from brands feel personalized and relevant to me	4.3723	0.68483
PP6. Personalized interactions make me feel valued as a customer	4.2314	0.81792
PC1. I am concerned that AI-driven systems might use my personal data in ways I cannot predict or control	4.1941	0.85919
PC2. I worry that the data I share with AI-driven platforms could be misused or exploited by companies	4.1569	0.82582
PC3. I feel uncertain about how AI-driven shopping platforms use my data to influence my purchasing decisions	4.2420	0.82458
PC4. I am concerned about protecting my information. When I know that there is an AI system on social media platforms, I regularly use	4.2527	0.77114
PB1. I tend to visit online sites for purchases that are AI-enabled	4.2101	0.72000
PB2. I make more purchases when brands offer personalized recommendations based on my preferences	4.2819	0.70827
PB3. I tend to buy products more often when I receive targeted ads that match my interests	4.1516	0.81053
PB4. I tend to increase my spending when I receive personalized discounts or offers	4.0239	0.85289
PB5. I am more likely to remain loyal to brands that use AI to personalize my shopping experience	4.1277	0.79979
PB6. I trust brands that use AI-driven insights to understand my needs and preferences	4.1011	0.91529
PB7. I make purchasing decisions faster when brands provide personalized recommendations	4.0186	0.87768
PB8. I spend less time comparing products when brands use AI to tailor their offerings to my preferences	4.1941	0.79804

Privacy Concerns (PC1–PC4) yielded moderate to high mean values (4.15–4.25, SD = 0.77–0.86), indicating that participants were cautious about data usage, although responses varied widely (e.g., PC1: SD = 0.86). Purchasing Behavior (PB1–PB8) exhibited slightly lower means (4.02–4.28, SD = 0.72–0.92), with PB4 (Mean = 4.02, SD = 0.85) and PB7 (Mean = 4.02, SD = 0.88) showing the weakest agreement, implying variability in how AI-driven insights translate to actual purchases.

4.1. Measurement Model Assessment

To evaluate the reliability and validity of the constructs, the measurement model was assessed through indicator loadings, internal consistency reliability, and convergent validity. As shown in Table 2, all indicator loadings exceeded the recommended threshold of 0.70, confirming adequate indicator reliability. Specifically, the loadings for AI-Driven Consumer Insights ranged from 0.760 to 0.896, Purchasing Behavior from 0.710 to 0.820, Perceived Personalization from 0.688 to 0.751, and Privacy Concerns from 0.843 to 0.896.

Table 2.
Reliability and Convergent Validity Assessment.

Construct	Indicators	Outer Loadings	Alpha	CR rho_A	AVE
AI-Driven Consumer Insights (AI)	AI1	0.760	0.885	0.923	0.684
	AI2	0.786			
	AI3	0.860			
	AI4	0.896			
	AI5	0.828			
Purchasing Behavior (PB)	PB1	0.710	0.911	0.916	0.615
	PB2	0.744			
	PB3	0.802			
	PB4	0.804			
	PB5	0.820			
	PB6	0.781			
	PB7	0.807			
	PB8	0.801			
Perceived Personalization (PP)	PP1	0.726	0.821	0.822	0.528
	PP2	0.688			
	PP3	0.734			
	PP4	0.734			
	PP5	0.751			
	PP6	0.725			
Privacy Concerns (PC)	PC1	0.896	0.888	0.918	0.746
	PC2	0.862			
	PC3	0.852			
	PC4	0.843			

Internal consistency reliability was verified through Cronbach's alpha and composite reliability (CR). All constructs exhibited Cronbach's alpha values greater than 0.80, and CR values exceeded the 0.70 benchmark, indicating high reliability. For instance, AI-Driven Consumer Insights (α = 0.885, CR = 0.923), Purchasing Behavior (α = 0.911, CR = 0.916), Perceived Personalization (α = 0.821, CR = 0.870), and Privacy Concerns (α = 0.888, CR = 0.922) all demonstrated strong internal consistency. Convergent validity was assessed using the average variance extracted (AVE), with all constructs achieving AVE values above the recommended threshold of 0.50 (Fornell & Larcker, 1981). Specifically, AVE scores were 0.684 for AI-Driven Consumer Insights, 0.615 for Purchasing Behavior, 0.528 for Perceived Personalization, and 0.746 for Privacy Concerns, confirming that the constructs capture a substantial portion of the variance of their indicators. Overall, the results indicate that the measurement model demonstrates satisfactory reliability and convergent validity, establishing a sound basis for subsequent structural model evaluation (Figure 2).

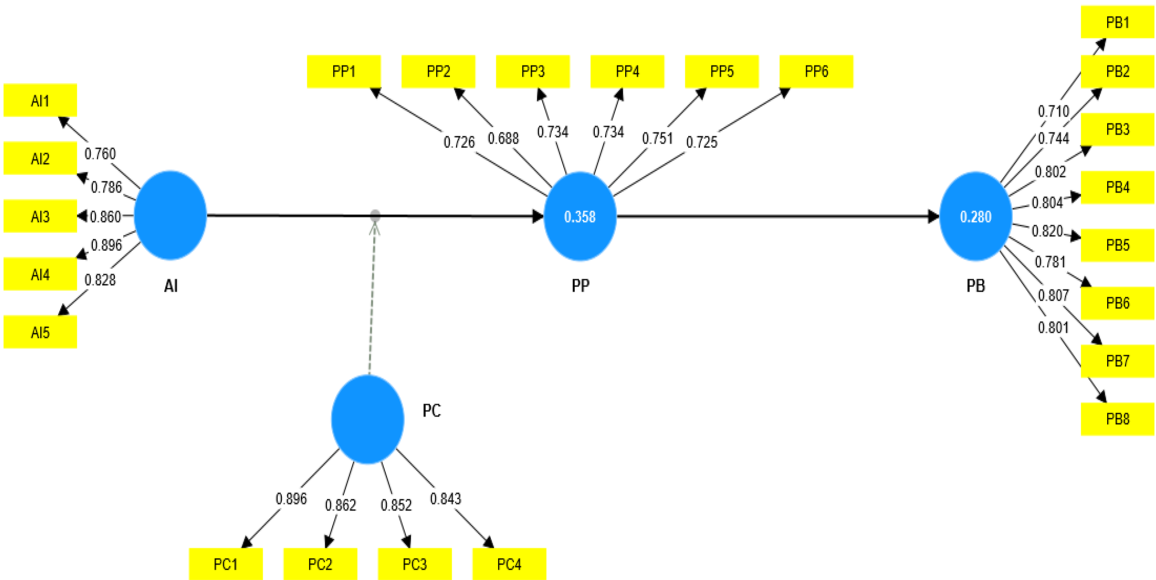

Figure 2.
Measurement Model.

4.2. Discriminant Validity HTMT Criterion

Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio of correlations, as recommended by Henseler, et al. [36]. Table 3 presents the HTMT values among all latent constructs. All HTMT values were below the conservative threshold of 0.85, indicating that each construct is empirically distinct from the others. These results provide strong evidence of discriminant validity among the study constructs.

Table 3.
HTMT Criterion.

	AI	PB	PC	PP
AI				
PB	0.224			
PC	0.275	0.367		
PP	0.457	0.604	0.565	

4.3. Structural Model Assessment

Before examining the path coefficients, collinearity among predictor constructs was evaluated using the Variance Inflation Factor (VIF). As shown in Table 4, all VIF values were well below the conservative threshold of 3.3 [40], suggesting that multicollinearity is not a concern in the structural model. Specifically, the VIF values were 1.079 for the path from AI to perceived personalization, 1.070 for privacy concerns to PP, and 1.000 for PP to PB. These results indicate that the independent variables are not excessively correlated, ensuring the robustness of the path coefficient estimates.

Table 4.
Collinearity Assessment (VIF).

	VIF <3.3
AI -> PP	1.079
PC -> PP	1.07
PP -> PB	1.00

The model's explanatory power, predictive relevance, and predictive accuracy were assessed using R^2, adjusted R^2, Q^2, and RMSE values as shown in Table 5.

Table 5.
Exploratory Power, Predictive Relevance, and Predictive Power.

Construct	R^2	R^2 Adj	Indicator	Q^2	PLS-SEM_RMSE	LM_RMSE
PB	0.280	0.278	PB1	0.043	0.706	0.716
			PB2	0.07	0.684	0.703
			PB3	0.08	0.779	0.797
			PB4	0.054	0.831	0.848
			PB5	0.104	0.758	0.771
			PB6	0.058	0.889	0.907
			PB7	0.091	0.838	0.83
			PB8	0.113	0.753	0.76
PP	0.358	0.353	PP1	0.215	0.687	0.68
			PP2	0.197	0.631	0.641
			PP3	0.112	0.713	0.699
			PP4	0.15	0.653	0.651
			PP5	0.179	0.621	0.629
			PP6	0.173	0.745	0.74

For explanatory power, the model explains 28.0% of the variance in Purchasing Behavior (PB) and 35.8% of the variance in Perceived Personalization (PP), indicating a moderate to strong explanatory capacity. The R^2 values align with typical social science research, confirming the model's adequate ability to explain both constructs. Regarding predictive relevance, both PB and PP meet the $Q^2 > 0$ threshold, with PP demonstrating stronger predictive relevance (ranging from 0.112 to 0.215) compared to PB (0.043 to 0.113).

For predictive accuracy, the RMSE values for PLS-SEM and linear regression are nearly identical, suggesting comparable predictive performance. PB indicators have moderate RMSE values (0.684–0.889), while PP indicators show stronger predictive accuracy (PLS-SEM RMSE: 0.621–0.745). Overall, the model exhibits reasonable explanatory power, stronger predictive relevance for PP, and comparable predictive accuracy to linear regression, which supports its robustness for out-of-sample prediction.

To verify the robustness of the measurement model, Confirmatory Tetrad Analysis (CTA) was applied to the four-item constructs [39]. The findings supported the reflective nature of their measurement, confirming the suitability of modeling these constructs as reflective. For the structural model, further robustness tests were conducted, including evaluations for non-linear effects, endogeneity [40], and unobserved heterogeneity. All tests produced satisfactory results, demonstrating that the structural model is free from significant biases and is robust for theoretical interpretation.

4.4. Hypotheses Testing (Bootstrapping)

The empirical findings provide robust support for the hypothesized relationships within the proposed conceptual framework (Table 6). Regarding H1, the results demonstrate that AI-driven consumer insights have a statistically significant and positive effect on the purchasing behavior of young consumers (β = 0.149, SD = 0.031, t = 4.853, p < 0.001). The 95% confidence interval [0.093, 0.213] confirms the reliability of this effect, indicating that the integration of AI technologies to generate consumer insights substantially enhances the likelihood of purchase decisions among young consumers.

Concerning H2, the analysis reveals a significant mediating role of perceived personalization in the relationship between AI-driven consumer insights and purchasing behavior. The indirect effect was positive and significant (β = 0.147, SD = 0.032, t = 4.851, p < 0.001), suggesting that AI-driven insights influence purchasing behavior not only directly but also indirectly through enhancing consumers' perceptions of personalization.

With respect to H3, the moderating effect of privacy concerns on the relationship between AI-driven insights and perceived personalization was statistically significant (β = –0.170, SD = 0.068, t = 2.493, p = 0.013). The negative interaction term, coupled with the confidence interval [–0.295, –0.027], supports the hypothesis that privacy concerns attenuate the positive influence of AI on perceived personalization. This finding suggests that while AI can enhance personalization, its effectiveness may be limited by consumers' concerns about data privacy, thereby highlighting the need for transparent and ethical data practices in AI-driven consumer engagement strategies.

Table 6.
Bootstrapping Results.

Path	B	SD	T	P values	2.50%	97.50%
AI -> PB	0.149	0.031	4.853	0.000	0.093	0.213
AI -> PP -> PB	0.147	0.032	4.851	0.000	0.092	0.211
PC x AI -> PP	-0.170	0.068	2.493	0.013	-0.295	-0.027

The interaction plot illustrates that the positive relationship between AI-driven consumer insights and perceived personalization is moderated by privacy concerns (Figure 3). Specifically, the effect of AI on perceived personalization is most potent when privacy concerns are low (red line) and weakest when privacy concerns are high (green line). This confirms that higher levels of privacy concern reduce the effectiveness of AI in enhancing perceived personalization, supporting the hypothesized moderation effect.

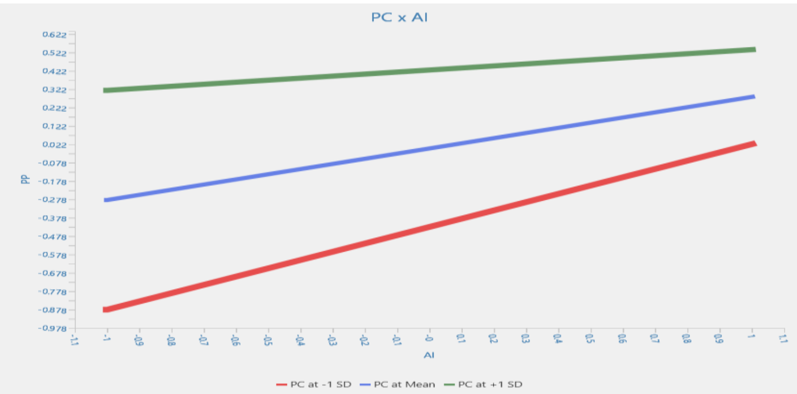

Figure 3.
The Interaction Plot.

The exploratory analysis revealed a significant moderated mediation effect, indicating that Privacy Concerns (PC) attenuate the indirect impact of AI-Driven Consumer Insights (AI) on Purchasing Behavior (PB) through Perceived Personalization (PP) (B = -0.147, SE = 0.059, p = 0.013). Specifically, as privacy concerns increase, the mediating role of PP in transmitting AI's influence on PB weakens, aligning with the earlier moderation finding (H3) where high PC reduces AI's ability to enhance PP. This highlights the dual role of privacy as both a boundary condition and a moderator, thereby diminishing the effectiveness of AI-driven strategies in creating personalized experiences and influencing subsequent purchasing decisions. The results highlight the importance of developing ethical AI frameworks that incorporate privacy safeguards (e.g., transparency, data control) to mitigate consumer skepticism and foster engagement, particularly among privacy-conscious segments. The results demonstrate that the indirect effect of AI-driven consumer insights (AI) on Purchasing Behavior (PB) through Perceived Personalization (PP) is contingent upon the level of Privacy Concerns (PC). At high PC (+1 SD), the conditional indirect effect is non-significant (B = 0.061, p = 0.218), indicating that AI-driven insights fail to meaningfully influence purchasing behavior via personalization when privacy concerns are elevated. Conversely, at low PC (-1 SD), the indirect effect is substantial and significant (B = 0.268, p < 0.001), suggesting that AI-driven personalization effectively drives purchasing decisions among consumers with minimal privacy concerns. At the mean level of PC, the indirect effect remains significant (B = 0.165, p < 0.001), highlighting that privacy concerns systematically attenuate, but do not entirely negate, the mediating role of PP. The findings of this study align with and extend previous research on AI-driven consumer insights and their impact on purchasing behavior. Prior research studies have established that AI-Driven Consumer Insights enhances personalized marketing strategies, leading to increased consumer engagement and purchase intentions [3, 19]. This study supports these findings, demonstrating a significant positive relationship between AI-driven consumer insights and the purchasing behavior of young consumers. However, the study also highlights the mediating role of perceived personalization, which was less emphasized in earlier works. While Humar [9] and Ingriana and Rolando [14] noted the importance of personalization in consumer engagement, this study quantifies its mediating effect, bridging a gap in the literature.

Additionally, the moderating role of privacy concerns aligns with the privacy calculus theory, Laufer, and recent studies by Nath [9] and Teepapal [24], which suggest that high privacy concerns can diminish trust in AI-driven personalization. This study empirically validates this interaction, showing that privacy concerns weaken the positive effect of AI-driven consumer insights on perceived personalization.

5. Theoretical and Practical Implications

This study contributes to the TAM model and privacy calculus theory by integrating them into a unified framework. While TAM emphasized perceived usefulness and ease of use [6], this study introduces perceived personalization as a mediator, demonstrating how AI-driven insights translate into observable purchasing behavior. The findings also advance the privacy calculus theory by showing how privacy concerns act as a boundary condition, moderating the effectiveness of AI-driven consumer insights. This aligns with recent calls for research on ethical AI deployment [2, 10] and underscores the need for theoretical models that account for privacy trade-offs in AI-driven marketing.

For practitioners, the study offers actionable insights. Businesses should leverage AI-driven consumer insights to create tailored experiences, as perceived personalization significantly mediates purchasing behavior. Moreover, transparency in data usage and ethical AI practices are critical to mitigating privacy concerns. Firms should implement clear privacy policies and opt-in mechanisms to build trust. Marketing campaigns should differentiate between privacy-sensitive and privacy-indifferent consumers, as privacy concerns moderate the effectiveness of AI-driven consumer insights.

6. Conclusion, Limitations, and Future Directions

The study confirms that AI-driven consumer insights have a positive influence on the purchasing behavior of young consumers, mediated by perceived personalization and moderated by concerns about privacy. It highlights the dual role of AI in enhancing personalization while necessitating robust privacy safeguards.

Regarding the limitations of this study, the sample was limited to Middle Eastern consumers, which may limit its generalizability. Moreover, Cross-sectional data may not capture the long-term dynamics of AI adoption. Future studies are encouraged to explore the longitudinal effects of AI-driven personalization on brand loyalty, investigate cultural variations in privacy concerns, and explore AI-driven consumer insights. Emerging technologies (e.g., blockchain) in addressing privacy concerns can also be examined.

References

[1] P. A. Okeleke, D. Ajiga, S. O. Folorunsho, and C. Ezeigweneme, "Predictive analytics for market trends using AI: A study in consumer behavior," *International Journal of Engineering Research Updates,* vol. 7, no. 1, pp. 36-49, 2024. https://doi.org/10.53430/ijeru.2024.7.1.0032

[2] N. Naveeenkumar, S. Rallapalli, K. Sasikala, P. V. Priya, J. Husain, and S. Boopathi, "Enhancing consumer behavior and experience through ai-driven insights optimization." Hershey, PA: IGI Global Scientific Publishing, 2024, pp. 1-35.

[3] A. T. Rosário and J. C. Dias, "AI-driven consumer insights in business: A systematic review and bibliometric analysis of opportunities and challenges," *International Journal of Marketing, Communication and New Media,* no. 15, 2025.

[4] M. T. Tran, "Unlocking the AI-powered customer experience: Personalized service, enhanced engagement, and data-driven strategies for e-commerce applications." Singapore: IGI Global Scientific Publishing, 2024, pp. 375-382.

[5] M. Paliwal and N. Chatradhi, "AI in market research: Transformative customer insights-A systematic review," *Exploring the Intersection of AI and Human Resources Management,* pp. 231-255, 2024. https://doi.org/10.4018/979-8-3693-0039-8.ch012

[6] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly,* vol. 13, no. 3, pp. 319-340, 1989. https://doi.org/10.2307/249008

[7] H. A. D. M. Arachchi and G. D. Samarasinghe, "Impulse purchase intention in an ai-mediated retail environment: Extending the tam with attitudes towards technology and innovativeness," *Global Business Review,* vol. 0, no. 0, p. 09721509231197721, 2023. https://doi.org/10.1177/09721509231197721

[8] R. Patil, K. Shivashankar, S. M. Porapur, and S. Kagawade, "The role of AI-driven social media marketing in shaping consumer purchasing behaviour: An empirical analysis of personalization, predictive analytics, and engagement," *ITM Web of Conferences,* 2024, vol. 68, p. 01032.

[9] S. Nath, "AI-driven personalization: Impact on consumer trust and purchase behaviour," *International Journal of Research Publication and Reviews,* vol. 6, no. 1, pp. 5110–5115, 2025.

[10] O. O. Joseph, A. S. Akintola, E. Offiong, O. O. Olajuwon, U. I. Offia, and A. A. Faniyan, "AI-enhanced consumer insights: Leveraging behavioural analytics for hyper-personalised marketing strategies," *Journal of Artificial Intelligence, Machine Learning and Data Science,* vol. 3, no. 1, pp. 2361–2368, 2025.

[11] R. I. Araf, "A systematic review of data-driven insights in retail: Transforming consumer behavior and market trend," *Innovatech Engineering Journal,* vol. 1, no. 01, pp. 46-55, 2024. https://doi.org/10.70937/itej.v1i01.6

[12] R. S. Laufer and M. Wolfe, "Privacy as a concept and a social issue: A multidimensional developmental theory," *Journal of social Issues,* vol. 33, no. 3, pp. 22-42, 1977. https://doi.org/10.1111/j.1540-4560.1977.tb01880.x

[13] S. Chowdhury, S. Basu, N. Ashoka, and P. K. Singh, "Influence of AI driven digital marketing on consumer purchase intention: An empirical study," *Journal of Informatics Education and Research,* vol. 4, no. 2, pp. 575-582, 2024. https://doi.org/10.52783/jier.v4i2.811

[14] A. Ingriana and B. Rolando, "Revolutioning e-commerce: Investigating the effectiveness of AI-driven personalization in influencing consumer purchasing behavior," *Jurnal Ilmiah Manajemen Dan Kewirausahaan,* vol. 4, no. 1, pp. 549-565, 2025.

[15] K. Mahmood, T. Tariq, A. K. Sangaiah, Z. Ghaffar, M. A. Saleem, and S. Shamshad, "A neural computing-based access control protocol for ai-driven intelligent flying vehicles in industry 5.0-assisted consumer electronics," *IEEE Transactions on Consumer Electronics,* vol. 70, no. 1, pp. 3573-3581, 2024. https://doi.org/10.1109/TCE.2023.3276066

[16] S. M. Babu, Prakash, P. P. Kumar, S. Devi, K. P. Reddy, and M. Satish, "Predicting consumer behaviour with artificial intelligence, *IEEE 5th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA)*, 2023, doi: https://doi.org/10.1109/ICCCMLA58983.2023.10346660.

[17] R. Al-Aqrabawi, B. Ismaeel, and K. K. Alafi, "The impact of AI-driven consumer insights on targeted marketing and customer retention strategies," *Pakistan Journal of Life and Social Sciences,* vol. 22, no. 2, 2024. https://doi.org/10.57239/pjlss-2024-22.2.00986

[18] K. A. Hamilton, S. Y. Lee, U. C. Chung, W. Liu, and B. R. Duff, "Putting the me in endorsement: Understanding and conceptualizing dimensions of self-endorsement using intelligent personal assistants," *New Media & Society,* vol. 23, no. 6, pp. 1506-1526, 2021. https://doi.org/10.1177/1461444820912197

[19] V. Kumar, B. Rajan, R. Venkatesan, and J. Lecinski, "Understanding the role of artificial intelligence in personalized engagement marketing," *California Management Review,* vol. 61, no. 4, pp. 135-155, 2019. https://doi.org/10.1177/0008125619859317

[20] M. Baldauf, P. Fröehlich, and R. Endl, "Trust me, I'ma doctor–user perceptions of AI-driven apps for mobile health diagnosis," *Proceedings of the 19th International Conference on Mobile and Ubiquitous Multimedia*, 2020.

[21] R. Bhagat, V. Chauhan, and P. Bhagat, "Investigating the impact of artificial intelligence on consumer's purchase intention in e-retailing," *Foresight,* vol. 25, no. 2, pp. 249-263, 2022. https://doi.org/10.1108/FS-10-2021-0218

[22] X. Dai and Q. Liu, "Impact of artificial intelligence on consumer buying behaviors: Study about the online retail purchase," *Journal of Infrastructure, Policy and Development,* vol. 8, no. 9, p. 7700, 2024

[23] Y. Amil, "The impact of AI-driven personalization tools on privacy concerns and consumer trust in e-commerce ", Master's Thesis, Université de Liège, Liège, Belgium, 2024.

[24] T. Teepapal, "AI-driven personalization: Unraveling consumer perceptions in social media engagement," *Computers in Human Behavior,* vol. 165, p. 108549, 2025. https://doi.org/10.1016/j.chb.2024.108549

[25] A. Kumari and P. Thakur, "Impact assessment of AI on consumer buying decisions," *EPRA International Journal of Economic and Business Review,* vol. 13, no. 3, pp. 71–77, 2025.

[26] J. Carmody, S. Shringarpure, and G. Van de Venter, "AI and privacy concerns: A smart meter case study," *Journal of Information, Communication and Ethics in Society,* vol. 19, no. 4, pp. 492-505, 2021. https://doi.org/10.1108/jices-04-2021-0042

[27] Y. Cheng and H. Jiang, "How do AI-driven chatbots impact user experience? Examining gratifications, perceived privacy risk, satisfaction, loyalty, and continued use," *Journal of Broadcasting & Electronic Media,* vol. 64, no. 4, pp. 592-614, 2020. https://doi.org/10.1080/08838151.2020.1834296

[28] F. I. Ahamed, "Revolutionizing retail: How artificial intelligence is transforming the customer experience," *Journal of Computer Science and Technology Studies,* vol. 7, no. 2, pp. 357-367, 2025.

[29] D. Sipos, "Theeffects of AI-powered personalization on consumer trust, satisfaction, and purchase intent," *European Journal of Applied Science, Engineering and Technology,* vol. 3, no. 2, pp. 14-24, 2025. https://doi.org/10.59324/ejaset.2025.3(2).02

[30] M. H. Shoukat, I. Elgammal, K. M. Selem, and A. E. Shehata, "Fostering social media user intentions: AI-enabled privacy and intrusiveness concerns," *Spanish Journal of Marketing - ESIC,* vol. 29, no. 2, pp. 253-269, 2024. https://doi.org/10.1108/sjme-07-2023-0205

[31] A. Kumar, G. Bapat, A. Kumar, S. L. Hota, G. D. Abishek, and S. Vaz, "Unlocking brand excellence: Harnessing AI tools for enhanced customer engagement and innovation," *Engineering Proceedings,* vol. 59, no. 1, p. 204, 2023. https://doi.org/10.3390/engproc2023059204

[32] A. K. Sharma and R. Sharma, "Assessing the influence of artificial intelligence on sustainable consumption behavior and lifestyle choices," *Young Consumers: Insight and Ideas for Responsible Marketers,* 2024. https://doi.org/10.1108/YC-09-2024-2214

[33] C. M. Ringle, S. Wende, and J.-M. Becker, *SmartPLS 4* Oststeinbek**,** Germany: SmartPLS GmbH, 2022.

[34] J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A primer on partial least squares structural equation modeling (PLS-SEM)*. Thousand Oaks: Sage Publications, 2021.

[35] J. F. Hair, M. Sarstedt, C. M. Ringle, and S. P. Gudergan, *Advanced issues in partial least squares structural equation modeling*. Thousand Oaks, CA: Sage Publications, 2023.

[36] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *Journal of the Academy of Marketing Science,* vol. 43, no. 1, pp. 115-135, 2015. https://doi.org/10.1007/s11747-014-0403-8

[37] N. Kock, "Common method bias in PLS-SEM: A full collinearity assessment approach," *International Journal of e-Collaboration (ijec),* vol. 11, no. 4, pp. 1-10, 2015.

[38] G. Shmueli, S. Ray, J. M. Velasquez Estrada, and S. Chatla, "The elephant in the room: Evaluating the predictive performance of partial least squares (PLS) path models," *SSRN Electronic Journal,* 2015. https://doi.org/10.2139/ssrn.2659233

[39] S. P. Gudergan, O. I. Moisescu, L. Radomir, C. M. Ringle, and M. Sarstedt, "Special issue editorial: Advanced partial least squares structural equation modeling (PLS-SEM) applications in business research," *Journal of Business Research,* vol. 188, p. 115087, 2025. https://doi.org/10.1016/j.jbusres.2024.115087

[40] A. Diamantopoulos and J. A. Siguaw, "Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration," *British Journal of Management,* vol. 17, no. 4, pp. 263-282, 2006. https://doi.org/10.1111/j.1467-8551.2006.00500.x