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The Impact of AI-Driven Personalized Marketing on Customer Loyalty: Evidence from the UK Retail Industry

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ARTICLE INFO	ABSTRACT
Received: 02 Sept 2025 Revised: 18 Oct 2025 Accepted: 28 Oct 2025	This study seeks to understand the impact of AI personalised marketing on customer loyalty in the UK retail sector. The study relies on the Stimulus–Organism–Response (S-O-R) theory, in which the personalized marketing via AI is considered to be an external stimulus affecting the behavioural response of customers by enhancing the retail experience. The study employed a quantitative, cross-sectional survey design, with 300 valid responses from UK retail consumers that had experienced AI-driven personalized marketing. SmartPLS software was used to analyze the data using Partial Least Squares Structural Equation Modelling (PLS-SEM). It was found that the effect of AI-driven personalized marketing on the customer loyalty is significant ($\beta = 0.954$, $p < 0.001$), has a large effect size ($f^2 = 10.064$), and has a high explanatory power ($R^2 = 0.910$). This research adds empirical evidence to the literature on AI marketing, as well as a contribution to the S-O-R framework. From a practical standpoint, the results suggest that retailers should embrace AI personalization in marketing startegies with a strategic approach, ensuring transparency, ethical data handling, and customer-centric implementation. **Keywords:** Artificial Intelligence, Personalized Marketing, Customer Loyalty, Retail Industry, UK.

INTRODUCTION

The retail sector has been making strides in the adoption of artificial intelligence (AI), but there is a question about whether AI-driven personalization marketing actually equates to loyal customers or not. With the growing adoption of AI in personalizing customer interactions in the UK retail sector, it is challenging and important to understand how AI affects customer loyalty, both academically and in practice. In the retail industry, AI is a key marketing tool, allowing retailers to tailor their messages, offers, prices and customer interactions in real-time through various digital channels (Beyari & Hashem, 2025; Sarwar & Malik, 2025). According to the UK Government, 1 in 6 UK businesses had adopted at least one AI technology (HM Government, 2025) and that top three business functions in which AI had been adopted were: marketing, customer service, and sales. Furthermore, the retailers are interested in utilising AI for CRM, recommendation systems and omnichannel marketing to drive a better customer experience and business outcomes. As the retail sector in the UK continues to digitalize rapidly, AI is becoming a vital resource for companies looking to maintain their competitive edge and deliver customised experiences to customers in an increasingly digital world (Wadud et al., 2024).

Policy makers have highlighted the opportunities and risks of AI and strengthened governance and regulation to ensure the responsible use of AI. Retailers in the UK use AI for personalised marketing which is governed by the UK General Data Protection Regulation (UK GDPR) and the Data Protection Act 2018, with the Digital Markets, Competition and Consumers Act 2024 providing enhanced consumer protection in the digital markets area (International Trade Administration, 2024). All these efforts work to promote transparency and respectful application of AI, protect consumer rights and ensure consumer trust in digital commerce. The Stimulus–Organism–Response (S-O-R) model (Mkpojiogu et al., 2024) underpinning this study posits that external environmental triggers can be used to influence the behavior of a person via internal cognitive and emotional assessment. In this study, the stimulus corresponds to the use of AI in personalized marketing, the response to customer loyalty, and the organism is treated in an abstract manner and not explored in detail.

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Although many retailers have made significant strides in implementing AI, there is evidence that many consumers are skeptical of AI-generated personalization. A 2025 survey conducted among 10,000 internet users (2000 from the UK) by the Usercentrics (2025), a privacy solution provider, reported that 58% of UK adults expressed concerns about how organizations use their personal information when delivering personalized services to train AI, while transparency regarding AI decision-making remained a major expectation among consumers. Equally, the Deloitte (2024) annual report of 2024 shows that consumers have become accustomed to a high level of personalization in their digital experiences, but they will only stick with personalization if it is helpful, not invasive. Such trends raise a key challenge for retailers in the UK: AI-driven personalization is becoming more common, but there is still some uncertainty about how positive customers feel about it, and whether it helps to build lasting loyalty.

Previous literature on AI-based personalisation has consistently shown its benefits in terms of customer loyalty (Abdullah, 2025; Hallikainen et al., 2022; Rane et al., 2024), but the literature consists of literature regarding online grocery retailing, conceptual literature, meta-analysis or marketing practitioners, excluding the UK retail consumers. As a result, there is limited empirical evidence that explores the direct connection between AI-driven personalized marketing and customer loyalty in the retail sector in the UK. The study does not address related matters like privacy, trust, or ethics; rather, it just looks at the direct impact of AI-driven personalized marketing on customer loyalty.

This study, therefore, seeks to explore how AI-driven personalized marketing strategies affect customer loyalty in the retail sector in the United Kingdom. The study has a theoretical contribution as it is extending the emerging AI marketing literature by examining this relationship in an empirical context in a contemporary UK retail setting, building on the theoretical foundation of the Stimulus–Organism–Response (S-O-R) framework. Practically, the results are expected to help retailers understand if AI personalization really improves customer loyalty, and the need to adopt AI-driven marketing strategies in a way that meets customer expectations and changing regulatory needs.

LITERATURE REVIEW

Key Constructs

Personalized marketing has been historically referred to as the act of targeting marketing communication, products, and promotional programs to specific customers depending on their traits, preferences, and behaviors (Chandra et al., 2022). Since the advent of artificial intelligence (AI), personalization has shifted beyond rule-based segmentation to intelligent systems that can analyze customer data in bulk and provide customers with highly personalized recommendations, offers, and shopping experiences in real-time. According to Ofosu-Ampong et al. (2025) and Iyelolu et al. (2024), the concept of AI-driven marketing refers to the use of artificial intelligence to automate marketing choices, create customer insights, and provide personalized customer interactions at multiple touchpoints. In the current research, AI-driven personalized marketing is operationalized as the degree to which UK retailers use artificial intelligence technologies to deliver customers with personalized marketing messages, product suggestions, promotions and online shopping experiences depending on their preferences and shopping behavior. This construct is measured through customers' perceptions of AI-driven personalization practices implemented by UK retailers.

One of the most researched concepts on relationship marketing is customer loyalty. Soderlund (2006) identified customer loyalty as a strong desire to repurchase or repatronize a favorite product or service in the future regardless of the situation and the marketing forces of the competitors. In the same way, Soderdlund et al. (2006) perceived customer loyalty as the positive behavioral intentions of the customers such as repeat purchasing, positive word of mouth, recommendation intentions, and opposition to switching of competitors. This research has defined customer loyalty as behavioral intentions of customers to remain in a long-term relationship with, recommend and purchase with UK retailers. The construct displays the readiness of consumers to be loyal to retailers when there is an opportunity to choose other rival competitors and is the main behavioral consequence of AI-driven personalized marketing.

Theoretical Framework

The current research is supported by the Stimulus-Organism-Response (S-O-R) Model, which was initially put forward by Mehrabian and Russell (1974, cited in Mkpojiogu et al., 2024). The S-O-R model describes that external environmental stimuli (Stimulus) affect the internal cognitive and emotional conditions of people (Organism) which in turn determine their behavioral responses (Response). Since the theory was developed, it has been widely used in retailing, consumer behavior, e-commerce, and digital marketing as an explanation on how environmental cues affect customer behavior.

In more recent works, scholars have embraced the S-O-R model in order to examine how customers react to AI-powered technologies, personalization, and online shopping experiences. As an example, the S-O-R model has been applied to the context of studies on AI-powered marketing, smart service technologies, and social commerce to explain the effect of technology-driven stimuli on customer appraisals and behavioral consequences, including customer engagement and loyalty (Imanuddin & Handayani, 2025; Jalalzadeh et al., 2025).

In the context of this paper, AI-driven personalized marketing serves as the Stimulus (S) since it is an external marketing practice that customers undergo. Customer loyalty is the Response (R) because it indicates customers intention to behave in such a way that they may maintain the relationship with UK retailers. Even though the Organism (O) component, which depicts the internal cognitive and affective judgments of customers, is not directly measured in the proposed research model, it is a significant theoretical mechanism, which elucidates the effects of AI-driven personalized marketing on customer loyalty. Thus, the S-O-R framework is a powerful theoretical framework to explain the relationship studied in this paper.

Hypothesis Generation

With machine learning, predictive analytics, and real-time data, AI has revolutionized retail marketing by creating more personalized customer experiences. While numerous benefits have been observed from the use of AI for personalized marketing, including improved relevance and customer experience, there are also challenges to consider, such as privacy concerns, trust issues, and ethical implementation. Although there are many positive impacts of AI in personalized marketing, such as enhanced relevance and customer experience, there are also challenges to consider, including privacy concerns, trust issues, and ethical implementation.

Existing literature suggests that AI-driven personalization is associated with customer loyalty and loyalty-related constructs by making marketing communications more relevant and customer-centric. In the context of online grocery retailing, personalization is seen as a way to change shopping convenience into a competitive advantage by lowering the cognitive effort of customers when they make a purchase (Hallikainen et al., 2022). Interestingly, they find that there is not a single personalization strategy that works best. Personalized price promotions appeared to have a significant, mitigating effect on the negative impact of cognitive effort on customer loyalty, but personalized product recommendations did not show a similar effect. It contradicts the widely accepted notion that any form of AI personalization has equal impacts on customer loyalty and indicates that customers might prefer the economic value of AI over algorithmic recommendations. Moreover, the study was limited to the online grocery retailing case, and the results may not be applicable to other retail industries, where customer decision making processes are significantly different.

Similarly, Rane et al. (2024) argues that customer satisfaction and customer experience (CX) can be enhanced by AI-powered personalization, which provides customers with tailored recommendations, intelligent customer relationship management (CRM), and proactive customer interactions, ultimately leading to increased customer loyalty. AI-based loyalty programs and predictive analytics can assist retailers in identifying customer behavior patterns indicative of a potential switch to another brand and implement targeted measures to retain customers, according to their review. The research is however rather conceptual in nature and focuses predominantly on the ability of the AI technologies but provides limited empirical evidence of customer response. The results of this study, therefore, further emphasize AI-based personalization as a strategic focus and still require empirical research with consumers.

Bhardwaj et al. (2024) hold a similar view, highlighting how AI can transform customer targeting by analyzing vast amounts of customer information and providing highly customised recommendations via machine learning, recommender systems, predictive analytics, and natural language processing. These technologies are shown to have a positive effect on conversion rates, cart abandonment and customer loyalty by providing more relevant shopping experiences, the authors report. Conversely, Bhardwaj et al. (2024) recognize that personalization in the retail sector, with the support of AI, should not be at the expense of ethical concerns, including transparency, informed consent,

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and responsible data handling. The study is mainly conceptual in nature and does not involve any empirical investigation, so the extent to which the recommendations can be implemented in terms of consumer loyalty is unknown.

More recently, there has been proof that technological progress is not enough to keep customers loyal in the long term. Al Prince et al. (2025) examined professionals' beliefs about the worth of AI for hyper-personalized marketing and found that the bulk favored using AI to improve customer segmentation, customized suggestions, and marketing outcomes. Meanwhile, the respondents identified data privacy, ethical concerns, implementation costs, and the absence of AI expertise as critical challenges to overcome when rolling out AI successfully. While the majority were optimistic about the potential future of AI in marketing, the study also found mixed views on how AI influences customer trust, indicating that innovation in technology can have a negative impact if the customer is not made aware of it, to build trust in the relationship. However, since the study gathered data from marketing professionals as opposed to actual retail customers, the results might not be a true reflection of customers' actual behavioral intentions.

Abdullah (2025) provides a broader synthesis of the literature, and his meta-nalysis of 52 studies suggests that the use of AI for personalization has always been shown to improve both transactional and emotional aspects of customer loyalty. Importantly, the review shows that the positive impacts of personalization on loyalty outcomes are largely accounted for by psychological mechanisms such as perceived relevance, trust, satisfaction, and emotional attachment. Moreover, the study suggests that long-term customer engagement is greatly enhanced by ethical AI practices and culturally adaptable personalization. Although it is a thorough synthesis, the review draws on a number of different sectors and countries, so it is unclear whether similar linkages are particular to the retail sector or to the UK.

Likewise, Kuma (2025) argues that predictive analytics and personalized marketing messages through AI can help marketers predict customer buying behavior, improve segmentation, and customize marketing messages to the individual's liking, which ultimately enhances customer loyalty. The review also warns of potential issues arising from algorithmic bias, privacy concerns, and loss of consumer trust which could impact the efficacy of AI marketing if not managed appropriately. The results are consistent with previous studies, which have highlighted that technological skills are not sufficient to keep customers loyal when they are not convinced that AI can deliver to them personalized and helpful information.

Overall, the current literature shows a general agreement on the potential for AI to contribute to increasing customer loyalty through more personalized, convenient and relevant shopping experiences. However, current research tends to have concentrated on a particular retail sector, on a conceptual or review based evidence or on marketing professionals as opposed to consumers, or in another context to the UK. As a result, there is a lack of studies that directly investigate customers' perception of AI personalized marketing within the UK retail sector. To fill this gap in context, the present study proposes the following hypothesis:

H: AI-driven personalized marketing is positively and significantly associated with Customer Loyalty

Literature Gap

While there is a vast amount of research regarding the use of AI for personalization, there are still a few key areas of research that have yet to be addressed. These previous studies have mainly focused on online grocery retailing (Hallikainen et al., 2022), conceptual discussions on AI marketing (Bhardwaj et al., 2024; Rane et al., 2024), systematic reviews and meta analyses (Abdullah, 2025; Kuma, 2025), or marketing professionals' perspectives (Al Prince et al., 2025) and therefore, the understanding of how retail consumers perceive AI-driven personalized marketing remains limited. Also, a significant proportion of the evidence is from outside of the UK, and is therefore less transferable to the retail sector in the UK. To fill these gaps, this study focuses on the direct link between AI-powered personalized marketing and customer loyalty from the UK retail consumers' point of view.

Conceptual Framework

The conceptual framework of this study is illustrated through Fig.1 below. It presents AI-Driven Personalized Marketing as independent variable, directly impacting dependable variable, which is Customer Loyalty.

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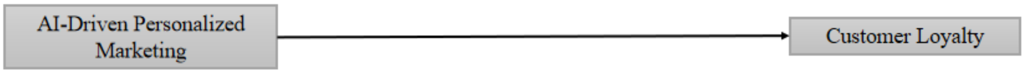

METHODOLOGY

Research Design

The paper has followed a quantitative research design where a cross-sectional survey was conducted to analyze how AI-driven personalized marketing has affected customer loyalty in the UK retail sector. The reason to choose a quantitative design was to have an opportunity to study the relationships between variables statistically and with the help of structured numeric data (Ghanad, 2023). The cross-sectional design is suitable because it involves data collection at one point in time, and suitable to explore their current perceptions and experiences with AI-driven personalized marketing practices used by UK retailers.

Data Collection Tool

A structured online questionnaire, created via Google Forms, was used to collect primary data. The online survey was chosen as it provides a cost-effective, fast and geographically diverse data collection among UK retail customers and provides the convenience and anonymity of respondents.

The questionnaire was divided into two parts (refer to Appendix). Section A was used to gather demographic details of the respondents such as gender, age, educational level, employment status, frequency of shopping and the channel of shopping of choice. In section B, the study constructs were measured in terms of five point Likert scale, with 1 being Strongly Disagree and 5 Strongly Agree. The AI-Driven Personalized Marketing construct was measured with five items based on personalization and AI marketing literature (Bankawat & Sharma, 2025; Iyelolu et al., 2024; Ofosu-Ampong et al., 2025) whereas Customer Loyalty was measured with five items based on the well-established customer loyalty scale developed by Mellens et al., (1996) and further supported by Soderdlund et al. (2006).

Sampling and Recruitmen*t*

A purposive sampling method and convenience sampling method were combined in this study. Purposive sampling is a non-probability sampling type where the respondents are identified based on the criteria that are of interest to the study goals, in contrast to convenience sampling where the respondents are those who are easily available to the researcher (Obilor, 2023). These methods were deemed to be suitable since the research was specifically focused on people who had previously experienced the shopping experience with the UK retailers that practice personalized marketing based on AI, including personalized product recommendations, customized promotional deals, and personalized digital messages.

The target group included customers aged 18 years and older who had previously purchased products with UK retailers via online or omnichannel platforms and received AI-driven personalized marketing. The respondents were recruited via the online platforms, social media tools (LinkedIn, Facebook, WhatsApp), the university network, professional acquaintances, and the online consumer communities. The survey link was sent out electronically where the respondents were given an opportunity to willingly take part after ascertaining that they fit the eligibility criteria.

About 380 invitations to questionnaires were sent. The response rate was about 85.8, and a total of 326 responses were obtained. The screening process of incomplete questionnaires, duplicates and responses that did not meet the eligibility criteria resulted into a total of 300 valid questionnaires to be analyzed.

The sufficiency of the sample size was also justified with the help of G* Power 3.1. Using a medium effect size (f^2 = 0.15) and significance level = 0.05, a statistical power of 0.95, and one predictor, the smallest needed sample size was significantly less than 300. Thus, the last sample was above the recommended value, which provided adequate statistical power in the case of Partial Least Squares Structural Equation Modelling (PLS-SEM).

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The weakness of the sampling method is that due to the use of non-probability sampling, results cannot be concluded to the whole population of the retail consumers in the UK with a hundred percent statistical certainty. However, this method is common in consumer behavior and marketing research where one needs a particular target population.

Data Analysis

The data were analyzed with the help of Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS software. PLS-SEM is a structural equation modelling method, based on variance, which tests the measurement model and the structural model simultaneously (Memon et al., 2021). It was chosen due to its suitability to predictive studies, theory testing, comparatively easy structural models, and survey data that do not necessarily meet multivariate normality requirements (Cepeda et al., 2024). The analysis was conducted in two phases: the first phase involved the measurement model reliability and validity, and the second phase entailed an appraisal of the structural model based on path coefficients, coefficient of determination (R^2), effect sizes (f^2) predictive relevance (Q^2), and bootstrapping significance tests.

Common Method Bias and Non-Response Bias

A number of procedural and statistical methods were used to reduce the likelihood of common method bias (CMB). Procedurally, respondents were guaranteed anonymity and confidentiality, their participation was voluntary, and the questionnaire had simple and unambiguous wording to minimize the evaluation apprehension and social desirability bias.

The single-factor test by Harman was a statistical post-hoc diagnosis test carried out to determine whether one latent factor explained most of the covariance between the measurement items, and this would demonstrate the occurrence of common method bias (Kock, 2020). The findings revealed that the initial unrotated measure had less than half of the total variance, implying that common method bias was not a major issue in this research. Moreover, Variance inflation factor (VIF) was also analyzed to identify full collinearity between the latent constructs. Kock (2025) explains that when the VIF is below 3.3, then the model is unlikely to be affected by common method bias, which will undermine its validity. The results indicated that the inner VIF values were less than the recommended level of 3.3, which justified that there was no significant common method bias (See Table 1).

Table 1: Full Collinearity VIF Values

	VIF
AI-Driven Personalized Marketing -> Customer Loyalty	1.000

In order to measure non-response bias, independent samples t-tests were used to compare responses obtained at the initial period of data collection, with those obtained at the later period. The analysis showed that there were no statistically significant differences between the early and late respondents with regard to the study variables ($p > 0.05$), which meant that non-response bias was not of concern.

Ethical Considerations

The research was conducted in accordance with ethical considerations. The entire participation was on a voluntary basis and the respondents were explained the aim of the study prior to filling the questionnaire. Informed consent was obtained electronically at the beginning of the survey. It was assured to the respondents that the information provided would be anonymous and confidential and would only be used in academic research. No personally identifiable data were taken, and the participants were not obligated to continue the survey until the end, and any withdrawals would not lead to any adverse consequences. All the data collected were safely stored and only used in this study.

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RESULTS

Descriptive Analysis

Table 2: *Demographics of 300 respondents*

Question	Response Options	Frequency	Percentage (%)
Gender	Male	117	39.0
	Female	164	54.7
	Prefer not to say	19	6.3
Age	18–24 years	58	19.3
	25–34 years	103	34.3
	35–44 years	74	24.7
	45–54 years	38	12.7
	55–64 years	27	9.0
Highest Education Qualification	High School or Equivalent	47	15.7
	Diploma / Certificate	59	19.7
	Bachelor's Degree	109	36.3
	Master's Degree	61	20.3
	Doctorate (PhD)	24	8.0
Employement Status	Employed Full-time	120	40.0
	Employed Part-time	36	12.0
	Self-employed	28	9.3
	Student	40	13.3
	Unemployed	25	8.3
	Retired	51	17.0
Shopping Frequency	Less than once a month	36	12.0
	Once a month	63	21.0
	Two to three times a month	78	26.0
	Once a week	74	24.7
	More than once a week	49	16.3
Shopping channels	Online only	96	32.0
	Physical stores only	45	15.0
	Both online and physical stores equally	159	53.0

The 300 subjects were grouped into the demographic profile as reflected in Table 2. The results show that the majority of the respondents were females (n = 164, 54.7%), followed by males (n = 117, 39.0%) and then those who did not

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prefer to disclose their gender (6.3%). Regarding age, most respondents were aged 25–34 years (n = 103, 34.3%), followed by 35–44 years (n = 74, 24.7%). The highest level of education was achieved by those who had a Bachelor's degree (n = 109, 36.3%). Most of the respondents (n = 120, 40.0%) were engaged in full time work. Regarding shopping habits, most were equally using online and off-line stores (N = 159, 53.0%) and most shopped 2-3 times a month (N = 78, 26.0%).

Measuremnet Model

Table 3: *Measurement Model*

Constructs	Indicators	Factor Loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
AI-Driven Personalized Marketing	AIPM1	0.964	0.957	0.961	0.854
	AIPM2	0.874			
	AIPM3	0.878			
	AIPM4	0.954			
	AIPM5	0.946			
Customer Loyalty	CL1	0.990	0.994	0.994	0.977
	CL2	0.985			
	CL3	0.993			
	CL4	0.985			
	CL5	0.989			

The measurement model results for AI-driven personalized marketing and customer loyalty are shown in Table 3. The thresholds for factor loading = 0.70, composite reliability = 0.70 and AVE = 0.50 representing the (Hair et al., 2019). All factor loadings were above the recommended value of 0.70 and varied between 0.874 and 0.964 for AI-driven personalized marketing and 0.985 and 0.993 for customer loyalty. The reliability results show that internal consistency was strong, the Cronbach's alpha and the composite reliability were > 0.70. In addition, the AVE values are 0.854 and 0.977, which are above the recommended value of 0.50, indicating acceptable convergent validity.

Discriminant Validity

Table 4: Discriminant Validity

	AI-Driven Personalized Marketing
Customer Loyalty	0.976

The results of the discriminant validity assessment based on the HTMT criterion are shown in Table 4. The HTMT value of AI-driven personalized marketing and customer loyalty was 0.976. The value does suggest strong association between the constructs but is high than a suggested lenient threshold of 0.90 for HTMT. Thus the criterion for discriminant validity is not completely met, and the constructs might exhibit some conceptual overlap and must be interpreted with caution.

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Model Fit

Table 5: Model Fit Summary

	Saturated model	Estimated model
SRMR	0.030	0.030
d_ULS	0.049	0.049
d_G	1.131	1.131
NFI	0.825	0.825

The model fit summary for the structural model is given in Table 5. The model fit is good (SRMR = 0.030) and is below the recommended value of 0.08. The d_ULS and d_G values were 0.049 and 1.131 respectively that showed acceptable model fit assessment values. The NFI value, however, is only 0.825, which is in the middle of the range and is not acceptable (0.90 or higher). The overall model fit is satisfactory for testing the hypotheses.

Path Coefficient

Table 6: Path Coefficient

	Path coefficient	T statistics	P values	f-square
AI-Driven Personalized Marketing -> Customer Loyalty	0.954***	206.627	0.001	10.064

The results of the structural model presented in Table 6 reveal that AI-driven personalized marketing has a very strong positive effect on customer loyalty ($\beta = 0.954$, $t = 206.627$, $p < 0.001$). The positive path coefficient indicates that there is a direct relationship between AI-driven personalized marketing and customer loyalty among UK retail consumers, meaning that as personalized marketing increases, customer loyalty also increases. Furthermore, the value of t is very high and the value of p is 0.001, which indicates that the proposed relationship is statistically supported well. The effect size ($f^2 = 10.064$) demonstrates the extremely large impact of AI-based personalized marketing on customer loyalty, as compared to the recommended values of effect sizes for a substantial effect. This indicates that personalized marketing using AI has a significant impact on the customer loyalty differences. So, H1 is accepted, and AI-powered personalized marketing is a notable and powerful predictor of customer loyalty.

Predictive Relevance and Explanatory Power

Table 7: R-Square and Q-Square

	R-square	R-square adjusted	Q^2predict
Customer Loyalty	0.910	0.909	0.909

The results of R-square and Q-square values for customer loyalty are shown in Table 7. The values of R^2 of 0.25 = weak, 0.50 = modest, and 0.75 = strong and $Q^2 > 0$ shows strong predictive relevance (Hossan et al., 2020). The R^2 value is 0.910, which means that the AI-driven personalized marketing accounts for 91.0% of the variance in customer loyalty, suggesting a high explanatory power based on the suggested criteria. The R^2 value is adjusted to 0.909, which is an additional indication of the strength of the model. Besides, Q^2 predict value of 0.909 is significantly greater than zero which indicates the high predictive relevance of the model. Therefore, the model is very explanatory and predictive.

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DISCUSSION

The findings confirm the importance and positive impact of AI-driven personalized marketing on customer loyalty among retail customers in the United Kingdom. But more significantly, the high level of relationship observed indicates that personalized marketing is becoming a more integral part of retail, and no longer just a marketing strategy. With the integration of AI in websites, mobile apps, and digital communication channels, customers are subjected to personalized recommendations, targeted promotions, and tailored shopping experiences continually. Hence, it is possible that consumers may no longer consider these practices as new technologies, but rather as an expression of a retailer's knowledge of customers' needs and wants. The perceived responsiveness is likely to reinforce the customers' intention to continue buying from the retailer and refer them to other customers, creating more customer loyalty.

Part of the reason for this is the evolving expectations of contemporary retail customers. Personalization is no longer a nice-to-have, but it's a key part of online retailing, especially in more technologically advanced markets like the United Kingdom. This personalization is not necessarily something consumers appreciate because it's new and exciting, but rather because it's something that helps them to decrease information overload, discover products and enables them to shop more efficiently. By leveraging AI, retailers can sift through vast amounts of customer data to provide marketing messages that are increasingly tailored to individual preferences, making the experience more relevant and convenient for customers. These are the kinds of experiences which can increase customer cognitive appraisals of the competence and the responsiveness of the retailer, and both of these are known relationship marketing antecedents of customer's long-term loyalty.

The results also offer an interesting look into how personalization is playing a role in retail today. Past studies have often highlighted that the success of AI-driven personalization relies on psychological factors like trust and satisfaction or perceived relevance (Abdullah, 2025). Such mechanisms are indeed relevant but the current results suggest that AI-driven personalized marketing is itself a powerful enough marketing practice to account for a significant proportion of the variance in customer loyalty. That is not to say that trust or satisfaction is not important, but it does mean that personalized marketing could have a direct effect on behavioral intentions if consumers equate personalized marketing with the overall superior shopping experience. As AI applications grow more sophisticated, customers might be less concerned about personalization as a technology and more concerned about personalization as a part of service quality.

The present results largely confirm and complement the available evidence. Personalized price promotions increased the degree of customer loyalty by lowering customers' cognitive effort, while product promotions alone yielded less because the products were not necessarily preferred (Hallikainen et al., 2022). Current study results indicate customers might not differentiate between separate AI features, but rather the entire personalization ecosystem set up by retailers. Similarly, Rane et al. (2024) and Bhardwaj et al. (2024) conceptualized that AI can improve customer relations through more intelligent and responsive marketing efforts. Current study aimed to offer empirical evidence for these claims, moving away from conceptual arguments, and to bolster confidence in the practical relevance of AI-driven personalized markting in today's retail environment.

Meanwhile, the findings are more optimistic than research focused on the potential dangers of using AI. Some factors were identified as potentially undermining customer acceptance of AI-driven personalized marketing, such as privacy concerns and ethical issues, as mentioned by Al Prince et al. (2025), as well as algorithmic bias, proposed by Kuma (2025). The lack of such concerns in the present study does not indicate that such concerns are unimportant, but rather it may be a reflection of the scope of the study. In the present study, the attention was specifically given to customer's evaluation of AI based personalized marketing and their loyalty intention, and not to privacy or ethical evaluations. Overall, the findings suggest that as consumers consider personalization mainly in relation to facilitation of shopping and relevance, the positive benefits are likely to outweigh the negative concerns. This is in line with recent industry data that indicates consumers are generally open to personalization that provides value and enhances experiences.

Findings can also be viewed as in the Stimulus–Organism–Response (S-O-R) paradigm. In this view, AI-driven personalized marketing can be considered an external environmental cue that can influence subsequent behavior.

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While the organism part was not directly measured, there was a relationship between the two, indicating that customers make favorable internal evaluations before declaring intentions of loyalty. That is, personalized marketing seems to promote positive cognitive appraisals of the retailer's understanding of customer needs, which in turn leads to repeat patronage and intentions to recommend the retailer. The present study does not try to add new constructs or extend the S-O-R framework, but instead shows that the theory is still very relevant to explain consumer's reactions to new marketing practices enabled by AI.

Lastly, the significant impact seen in this study must be understood in the light of the study, and not as proof that AI is the only factor in customer loyalty. Customer Loyalty is a phenomenon that is multifaceted and is created through the interplay of many marketing and relational/service related factors. However, the results are clear, as AI-driven personalized marketing has become a key strategic tool in today's retailing landscape. Based on the current results, it, therefore, strengthens the perspective that AI should not just be seen as an operational technology, but as one that can impact tangible customer actions.

THEORETICAL CONTRIBUTION

This study adds to the growing body of literature on AI marketing in providing empirical evidence that AI-driven personalized marketing acts as an effective external marketing stimulus that can impact customer loyalty in the UK retail industry. Prior studies have mostly been conceptual, systematic reviews, meta-analysis or sector specific studies, but this work seeks to validate the proposed relationship using primary consumer data gathered from retail customers in the UK. Moreover, the results support the use of the S-O-R model in understanding consumer behavior by showing that a response may be directly explained by the presence of AI-driven personalized marketing, even if the organism component is not explicitly operationalized. The study further provides contextual evidence from the UK retail sector, where there is relatively limited empirical research on the effects of AI-driven personalized marketing. The results thus reinforce the theoretical understanding of AI personalization as a marketing stimulus that can have a positive impact on customer loyalty in digitally enabled retail environments.

CONCLUSION

This research proves that AI-driven personalized marketing is one of the most important factors influencing customer loyalty among the retail customers in the UK. The results confirm the significance of the personalization strategy in today's retail and offer empirical evidence in the UK context. With the growing integration of AI in retail marketing, customer engagement with personalized experiences will continue to play a pivotal role in driving sustainable, customer-centric marketing strategies.

IMPLICATIONS

The results indicate that AI-driven personalized marketing could be an effective approach for UK retailers to boost customer loyalty, but it must be done cautiously. The robust relationship found does not mean that AI-driven personalized marketing is a cure-all for long-term loyalty, especially considering that the personalization and loyalty constructs may overlap. Retailers should thus not exclusively trust algorithmic recommendations, and make sure that personalization is adding value for the customer. Data transparency, customer control over personalization preferences, and ethical AI practices are still to be taken into account. To achieve sustainable relationship outcomes, retailers should explore AI initiatives, customer trust, customer satisfaction and perceived usefulness.

LIMITATIONS AND FUTURE RESEARCH DIRECTION

It is important to address some drawbacks of this study. Firstly, a cross-sectional design cannot draw causal claims about change in customer loyalty over time. Secondly, the non-probability sampling method used may mean that the results are not representative of the broader retail population in the UK. Third, AI-driven personalized marketing showed a robust positive relationship with customer loyalty, whereas the HTMT value was 0.976, which is slightly higher than the recommended value of 0.90, suggesting that there may be some conceptual overlap between the constructs and thus careful interpretation is required. Further, the very large effect size (f^2 = 10.064) indicates a strong predictive association, which can either be due to the absence of other explanatory factors or due to overlap in the scale. Future studies should thus further elaborate the indicators of the constructs and expand the dimensions of AI-driven personalized marketing to include perceived relevance, customer scepticism, transparency, and perceived

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intrusiveness. Future research could also include more longitudinal and probability-based designs and the examination of mediating or moderating factors, such as trust, satisfaction, perceived value, privacy concerns and customer attitudes to AI, for a more thorough understanding of the impact of AI-driven personalized marketing on customer loyalty.

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Appendix

Questionnaire

Section A: Demographics

Question	Response Options
D1. Gender	1. Male 2. Female 3. Prefer not to say
D2. Age	1. 18–24 years 2. 25–34 years 3. 35–44 years 4. 45–54 years 5. 55–64 years
D3. Highest Educational Qualification	1. High School or Equivalent 2. Diploma / Certificate 3. Bachelor's Degree 4. Master's Degree 5. Doctorate (PhD)
D4. Employment Status	1. Employed Full-time 2. Employed Part-time 3. Self-employed 4. Student 5. Unemployed 6. Retired
D5. How often do you shop from UK retailers that use AI-driven personalized marketing?	1. Less than once a month 2. Once a month 3. Two to three times a month 4. Once a week

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	5. More than once a week
D6. Which shopping channel do you use most frequently?	1. Online only 2. Physical stores only 3. Both online and physical stores equally

Section B: Main Questionnaire

Note: Please indicate your level of agreement with the following statements based on your overall experience with UK retailers that use AI-driven personalized marketing (e.g., personalized product recommendations, tailored emails, mobile app notifications, or customized promotions).

Response Scale (for all items):

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Construct & Items	5-Point Likert Scale
AI-Driven Personalized Marketing (IV)	
AIPM1. UK retailers use AI technologies to personalize their marketing communications.	1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
AIPM2. UK retailers provide AI-generated product recommendations based on customer information.	1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
AIPM3. UK retailers customize promotional offers using customers' shopping behavior.	1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
AIPM4. UK retailers tailor the content displayed on their websites, mobile apps, or emails according to customer preferences.	1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
AIPM5. UK retailers use AI to create personalized shopping experiences for customers.	1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
Customer Loyalty (DV)	
CL1. I intend to continue purchasing from UK retailers that I regularly shop with.	1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
CL2. I would recommend my preferred UK retailer(s) to friends or family.	1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
CL3. My preferred UK retailer(s) would be my first choice when purchasing similar products.	1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
CL4. I would continue shopping with my preferred UK retailer(s) even if competitors offered similar products or prices.	1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
CL5. I consider myself loyal to my preferred UK retailer(s).	1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐