Understanding the Loyalty Effects of AI-driven Personalisation: Consumer Engagement as a Mediator and Algorithmic Trust as a Boundary Condition

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Abstract

As digital platforms increasingly rely on AI-driven personalisation, growing evidence suggests that improvements in algorithmic efficiency do not automatically translate into stronger brand loyalty. Addressing this disconnect, this study examines how AI-driven personalisation influences brand loyalty in digital platform contexts, with particular attention to the mediating role of consumer engagement and the moderating role of algorithmic trust. Drawing on a relational value-creation perspective, a conceptual model is developed to explain how technological personalisation is transformed into relational outcomes under different trust conditions. Using a quantitative, cross-sectional design, data were collected from 398 digital platform users through a structured questionnaire based on established measurement scales. Partial least squares structural equation modelling (PLS-SEM) was employed to test the proposed model after confirming measurement reliability, validity, and the absence of serious common method bias. The results show that AI-driven personalisation has a significant positive effect on brand loyalty and strongly enhances consumer engagement, which in turn positively influences brand loyalty and partially mediates the personalization-loyalty relationship. Furthermore, algorithmic trust emerges as a critical boundary condition, significantly strengthening both the effect of AI-driven personalisation on consumer engagement and the effect of consumer engagement on brand loyalty. These findings suggest that personalisation generates relational value not merely through technical accuracy, but through its capacity to activate consumer engagement within a trusted algorithmic environment. By integrating consumer engagement and algorithmic trust into a unified framework, this study advances existing research on AI-enabled marketing and brand loyalty and provides practical insights for digital platforms seeking to align personalisation strategies with long-term relationship building.

Keywords

AI-driven personalization, Brand loyalty, Consumer engagement, Algorithmic trust, Digital platforms, Partial least squares structural equation modelling

Introduction

Research background

As digital platforms have become the dominant commercial infrastructure, AI-driven personalisation is propelling the ways in which brands are seen, understood, and chosen into a new stage of development. At the macro level, corporate investment in artificial intelligence has shifted from exploratory pilot projects to large-scale deployment. According to IDC's expenditure forecasts, global spending on AI-centric systems reached approximately USD 154 billion in 2023 and is expected to exceed USD 300 billion by 2026, a growth trajectory that clearly indicates AI's transition into a core component of business operations across industries [1].

At the meso level, personalisation is evolving from a narrow focus on recommendation systems toward a broader operational logic, becoming deeply embedded in digital platforms' content distribution, product ranking, interface presentation, and service interactions. As a result, brand reach increasingly depends less on homogeneous mass exposure and more on algorithms' dynamic identification of individual preferences and contextual signals. Research by McKinsey further highlights the commercial value underlying this shift, showing that personalisation in marketing and growth contexts can generate a 10%-30% uplift in marketing ROI and substantially enhance revenue performance [2].

At the micro level, platform practices render such "computable differentiated experiences" tangible and observable. Studies of Netflix's recommendation system demonstrate that a substantial proportion of viewing behaviour on the platform is driven by personalised recommendations. These systems do not merely "push content to users", rather, they continuously shape users' viewing trajectories and rhythms of experience [3]. Within the Chinese context, the massive user base and high degree of mobile penetration provide particularly fertile ground for the application of personalisation technologies. According to CNNIC, by the end of 2023 China's internet population had reached 1,092 billion, with 1,091 billion mobile internet users, and 99.9% of users accessing the internet via mobile devices. In such a high-frequency, fragmented, and context-rich environment of consumption and content engagement, practices such as Douyin's feed-based content distribution, Xiaohongshu's interest-content matching, and e-commerce platforms' intelligent customer service and recommendation explanation systems are transforming personalisation from a backstage algorithmic capability into a frontstage, perceptible user experience.

It is precisely for this reason that discussions of AI-driven personalisation can no longer be confined to questions of technological upgrading. Instead, they must address how brand-consumer relationships are being reorganised within digital platform contexts, and why relational outcomes such as brand loyalty may exhibit new formation logics and evolutionary paths under this emerging mechanism.

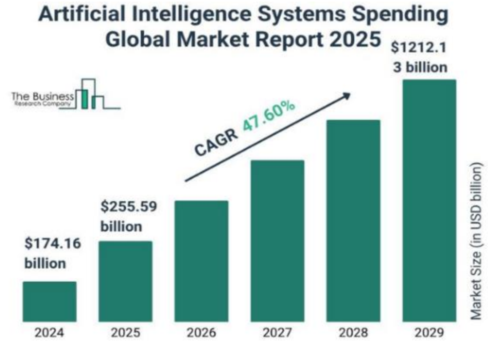

Figure 1. Spending Artificial Intelligence Systems global market report 2025.

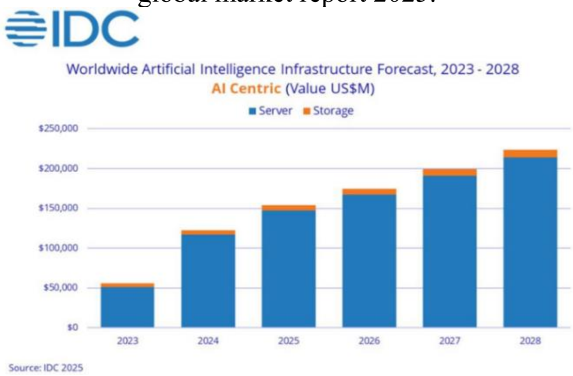

Figure 2. Worldwide artificial intelligence infrastructure forecast, 2023-2028.

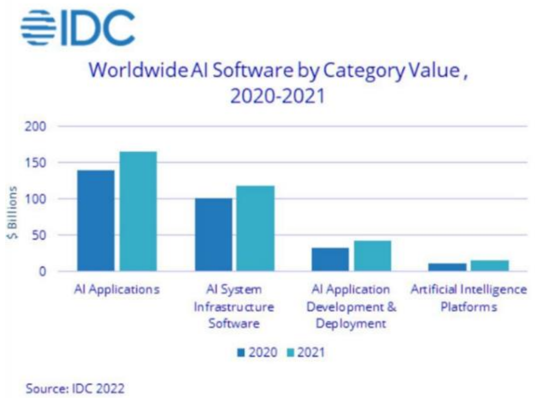

Figure 3. Worldwide Al software by category value, 2020-2021.

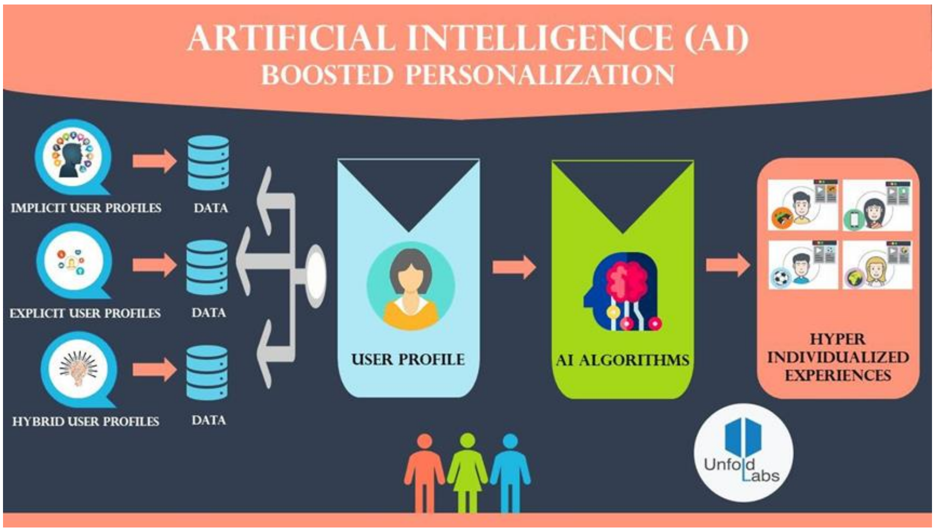

Figure 4. Transformation of marketing models from “mass communication” to “data-driven precision interaction”.

Figure 5. Netflix personalized covers and recommendation interface, and amazon personalized product recommendation interface.

Problem statement

In business environments dominated by digital platforms, brand loyalty is increasingly exhibiting a fragile pattern that does not correspond to the intensity of firms' technological investments. Despite substantial and sustained investment in algorithms, data infrastructures, and personalisation systems, consumers' long-term attachment to brands has not strengthened accordingly. On the contrary, evidence across multiple industries suggests a persistent erosion of brand loyalty. Recent surveys indicate that digital consumers are switching brands more frequently, with loyalty behaviour increasingly manifesting as situational choice rather than stable relational commitment. Deloitte's Global Consumer Study (2023-2024) reports that even when overall consumer satisfaction remains relatively high, more than half of respondents switched their primary brand within a single year. In digital platform contexts, low switching costs have significantly weakened brand lock-in effects. This tendency is particularly pronounced in platform-based industries, where consumers rapidly migrate across brands and platforms in response to recommendation outputs, real-time pricing, and content-interest matching. As a result, brand loyalty is gradually compressed into a passive response to short-term experiences and convenience.

For firms, the consequences of this trend extend far beyond the loss of individual transactions to encompass a systemic decline in customer lifetime value. Desveaud consistently emphasises that a 5% decrease in customer retention can reduce long-term profits by 25%-95%. In highly competitive digital markets, where customer acquisition costs continue to rise, weakened loyalty directly undermines the foundations of sustainable growth [4]. More subtly, brand churn on digital platforms often exhibits a "silent" pattern - users do not necessarily express dissatisfaction through complaints or negative feedback but instead disengage quietly or shift to alternative brands. This silent defection makes it difficult for firms to identify the true causes of relational breakdowns in a timely manner.

As this loyalty crisis accumulates at the industry level, its consequences extend beyond the performance of individual brands and may evolve into structural risks within platform ecosystems. On the one hand, brands increasingly rely on promotions, subsidies, and paid traffic acquisition to compensate for declining loyalty, resulting in rigidly rising marketing costs. On the other hand, consumers develop a "use-and-switch" mindset in algorithm-driven information environments, making it difficult for brands to achieve differentiation through long-term relationships. Prior research suggests that in highly algorithmised markets, brands that fail to establish stable emotional and trust-based foundations see their competitive advantages rapidly imitated and diluted, ultimately becoming trapped in exhaustive competition centered on price and exposure [5]. If this trajectory continues, digital platforms may cease to function as mechanisms for accumulating brand value and instead become amplifiers of rapid relational turnover and continuous value erosion - an outcome that directly contradicts firms' original intentions in investing heavily in AI-driven personalisation.

A closer examination of the roots of this crisis reveals that the core problem lies not in whether firms adopt AI-driven personalisation, but in the structural limitations embedded in how personalisation operates in practice. Most current platform personalisation systems are centered on behavioural data and algorithmic prediction. While they are highly effective at identifying what consumers do, they are far less capable of addressing why consumers are willing to continue choosing a particular brand. A substantial body of empirical research indicates that algorithm-driven personalisation tends to prioritise short-term performance indicators such as click-through rates, dwell time, and immediate conversion.

This efficiency-oriented logic may strengthen the instrumental nature of consumption decisions, yet it does not necessarily facilitate the formation of emotional bonds or psychological commitment [6]. At the same time, the "black box" nature of personalisation systems has intensified consumer unease. According to the Edelman Trust Barometer (2024), only around half of respondent's express trust that companies use their data responsibly, and the lack of explanation for algorithmic decisions is widely perceived as a key factor undermining brand trust [7].

When consumers cannot understand why personalised content appears or assess whether it serves their own interests, precision targeting may be interpreted as manipulation or intrusion, thereby exerting a negative influence on brand relationships. More importantly, existing research often remains at the level of technological performance or perceived value when explaining why personalisation fails to translate effectively into brand loyalty, while paying insufficient attention to the underlying psychological and relational mechanisms.

On the one hand, consumer engagement, an essential mediator linking brand stimuli to relational outcomes - is not an automatic by-product of personalisation initiatives. Prior studies demonstrate that engagement translates into deeper relational bonds only when consumers experience a sense of agency, involvement, and opportunities for value co-creation during interactions [8]. However, in highly algorithmised contexts, consumers are frequently positioned as passive recipients of recommendations and guidance. Resulting in engagement that is reactive rather than participatory and therefore insufficient to sustain long-term loyalty. On the other hand, algorithmic trust, as an emerging form of institutional trust, has become a critical boundary condition shaping how personalisation affects brand relationships. Recent research shows that perceived algorithmic transparency, explainability, and fairness significantly enhance users' trust in algorithmic systems, and that this trust can further transfer to the brands deploying such systems, thereby influencing relationship satisfaction and loyalty intentions [9]. Nevertheless, these variables are often examined in a fragmented manner and have yet to be systematically integrated and tested within a unified analytical framework.

Accordingly, the brand loyalty crisis observed in contemporary digital platform contexts cannot be attributed solely to intensified competition or shifting consumer preferences. Rather, it emerges from the combined effects of the application logic of AI-driven personalisation, the absence of effective mediating mechanisms, and insufficient trust conditions. If personalisation continues to be treated as a technological tool that directly drives loyalty, while neglecting the processual role of consumer engagement and the critical contextual constraints imposed by algorithmic trust - the disconnect between technological investment and relational returns is unlikely to be resolved. Against this backdrop, a structured examination of how AI-driven personalisation influences brand loyalty through consumer engagement, and how algorithmic trust moderates this process, is not only theoretically necessary but also provides urgently needed empirical evidence for the sustainable governance of brand relationships in the digital platform era [10].

Based on the above discussion, this study proposes the following research questions and objectives:

RQ_1: How does AI-driven personalisation influence consumers' brand loyalty in digital platform contexts?

RQ_2: Does consumer engagement mediate the relationship between AI-driven personalisation and brand loyalty?

RQ_3: Does algorithmic trust moderate the strength of the effect through which AI-driven personalisation influences brand loyalty via consumer engagement?

RO_1: To examine the direct impact of AI-driven personalisation on consumers' brand loyalty in digital platform contexts.

RO_2: To analyse the mediating mechanism of consumer engagement in the relationship between AI-driven personalisation and brand loyalty.

RO_3: To explore the moderating role of algorithmic trust in the relationships among AI-driven personalisation, consumer engagement, and brand loyalty.

Literature review and research hypotheses

Literature review

As digital platforms have increasingly become the primary arenas for brand-consumer interaction, scholarly interest in how AI-driven personalisation reshapes brand relationships has continued to intensify. Existing studies widely agree that algorithmic recommendation systems, intelligent content distribution, and automated services have fundamentally altered consumers' decision environments, shifting brand communication from homogeneous mass messaging toward highly differentiated and context-sensitive interaction patterns [11]. Against this backdrop, personalisation is no longer regarded as a single marketing instrument but rather as a core mechanism embedded within platform operating logics. Its role has expanded from influencing isolated choices to shaping ongoing relational dynamics. While a growing body of research confirms that AI-driven personalisation significantly affects consumer attitudes, perceived value, and usage experiences, there is still substantial disagreement on two key points: Whether these effects can be translated into stable brand loyalty, and the specific mechanisms through which this translation would occur.

From a developmental perspective, the existing literature can broadly be organised into three major streams. The first stream adopts a technological and performance-oriented perspective, emphasising the advantages of algorithms in matching efficiency and decision support. Research within this stream typically draws on information processing and recommender system theories, suggesting that personalisation reduces search costs, enhances decision convenience, and improves short-term outcomes such as satisfaction and purchase intention [12]. However, this perspective tends to conceptualise consumers as passive recipients of information and focuses primarily on whether more accurate recommendations lead to higher conversion rates, offering limited insight into the long-term evolution of brand relationships.

The second stream introduces consumers' subjective experiences and psychological responses, situating personalisation within broader discussions of brand relationships and customer experience. Studies in this tradition indicate that personalisation positively influences brand attitudes only when it is perceived as useful, relevant, and non-intrusive. Aguirre further argues that in multi touchpoint customer journeys, brand value emerges from continuous interaction experiences rather than isolated stimuli. This line of research shifts attention from technical performance to relational processes. Nevertheless, its limitation lies in the tendency to treat personalisation and brand loyalty as directly linked, implicitly if improvements in experience will naturally accumulate into loyalty over time [13].

The third stream focuses on emerging issues associated with platformisation and algorithmic governance, particularly trust, transparency, and ethical risks. As AI becomes deeply embedded in content distribution and decision guidance, consumers' concerns regarding algorithmic motives and data usage practices have intensified. Prior research demonstrates that algorithmic opacity can undermine consumers' trust in platforms and the brands operating within them, thereby offsetting the positive experiential effects of personalisation. More recent studies suggest that algorithmic trust is not merely confidence in technical performance but a form of relational trust that combines cognitive evaluation with institutional expectations. Importantly, such trust may transcend specific systems and transfer to the brand level [14]. While this perspective provides valuable insights into the heterogeneous effects of personalisation, empirical evidence remains fragmented, and a stable explanatory framework has yet to be established.

Within these research streams, brand loyalty has emerged as a particularly complex dependent variable. Traditional studies often conceptualise loyalty in terms of repeat purchase behaviour or attitudinal preference. However, in digital platform contexts, loyalty increasingly manifests as a dynamic outcome formed through ongoing comparison and choice among multiple alternatives. Extensive research has shown that satisfaction and perceived value, although important antecedents, are insufficient to explain the long-term stability of loyalty - especially in environments characterised by low switching costs and high information transparency [15]. This suggests that efficiency gains or experiential enhancements alone, even when facilitated by personalisation, are unlikely to adequately address the observed erosion of brand loyalty.

Against this backdrop, consumer engagement has gained prominence as a critical mechanism linking brand stimuli to relational outcomes. Brodie conceptualise consumer engagement not merely as behavioural interaction frequency but as a psychological state encompassing cognitive, emotional, and behavioural investment. Subsequent studies demonstrate that engagement deepens brand relationships through perceived co-creation and self-relevance, serving as an important mediating pathway in loyalty formation Hollebeek. However, within AI-driven personalisation environments, it remains unclear whether consumers genuinely engage or are simply “carried along” by algorithmic guidance. Most existing studies implicitly assume that personalisation automatically stimulates engagement, while paying insufficient attention to the distinction between passive response and active involvement.

At the same time, the importance of algorithmic trust as a contextual moderator has become increasingly evident. Prior research indicates that when consumers perceive algorithmic decision-making processes as fair, explainable, and aligned with their interests, their overall evaluations of both the platform and the associated brand improve significantly. Conversely, when algorithms are perceived as manipulative or opaque, even highly accurate recommendations may trigger resistance and undermine relational foundations. This implies that personalisation does not influence loyalty through uniform pathways across all contexts, rather, its effects are highly contingent on trust conditions. Despite this insight, such boundary mechanisms have not yet been fully integrated into existing empirical models [16].

In summary, although extant research provides an important foundation for understanding AI-driven personalisation, consumer responses, and brand relationships, several limitations remain. First, personalisation is predominantly treated as a direct stimulus, with insufficient attention paid to the processual mechanisms through which it operates via consumer engagement. Second, although algorithmic trust is frequently acknowledged, it is often examined as a background factor or a simple antecedent, rather than as a systematic moderating condition. Third, within the core context of digital platforms, the logic underlying brand loyalty formation has yet to be integrated into a unified structural model. Accordingly, building on prior research, it is necessary to introduce consumer engagement as a mediating mechanism and incorporate algorithmic trust into the analytical framework to systematically examine the pathways and boundary conditions through which AI-driven personalisation influences brand loyalty in digital platform contexts.

Research hypotheses and conceptual framework

Within digital platform contexts, AI-driven personalisation is widely regarded as a critical technological mechanism for reshaping brand relationships. Prior research indicates that through continuous algorithmic learning of consumers’ preferences, behavioural trajectories, and contextual signals, personalisation significantly enhances information matching accuracy and decision convenience, thereby improving consumers' overall evaluations of brands. From a relationship marketing perspective, when brand-provided content, services, and interaction modes are perceived as highly relevant and useful, consumers are more likely to develop favourable attitudes and repeated choice tendencies - both of which constitute essential preconditions for brand loyalty. In digital platform environments, personalisation extends beyond a discrete marketing tool to become a foundational mechanism embedded throughout the entire consumer journey of exposure, usage, and interaction. Its cumulative effects may therefore exert a direct influence on brand loyalty [17]. Based on these theoretical and empirical foundations, the following hypothesis is proposed:

H_1: In digital platform contexts, AI-driven personalisation has a significant positive effect on brand loyalty.

Although personalisation can enhance matching efficiency, whether it translates into stable brand loyalty depends on whether consumers develop sustained involvement during their interactions with the brand. Consumer engagement theory posits that engagement is not merely reflected in behavioural interaction frequency but represents a psychological state encompassing cognitive, emotional, and behavioural investment. Its core lies in whether consumers actively integrate themselves into the brand relationship. Existing studies demonstrate that when brand interactions are perceived as personalised and responsive, consumers are more likely to experience engagement and a sense of value co-creation, which in turn strengthens emotional attachment and commitment to the brand. In AI-driven personalisation contexts, algorithmic recommendations, intelligent services, and dynamic content presentation provide new triggers for engagement. However, whether engagement is genuinely activated remains a critical process variable linking personalisation and loyalty. Accordingly, it is necessary to examine consumer engagement from a mediating perspective, leading to the following hypotheses:

H_2: AI-driven personalisation has a significant positive effect on consumer engagement.

H_3: Consumer engagement has a significant positive effect on brand loyalty.

Building on the above reasoning, AI-driven personalisation can be expected to influence brand loyalty not directly, but indirectly by enhancing consumers' level of engagement during interactions. On this basis, the following mediation hypothesis is proposed.

H_4: Consumer engagement mediates the relationship between AI-driven personalisation and brand loyalty.

As AI becomes increasingly embedded in digital platforms, consumers' trust in algorithmic systems has emerged as a crucial contextual factor shaping the effectiveness of personalisation. Algorithmic trust involves not only cognitive judgments regarding technical accuracy but also institutional expectations concerning algorithmic motives, fairness, and data usage practices [18]. Prior research indicates that when consumers perceive algorithmic decision-making processes as transparent, explainable, and aligned with their own interests, their overall trust in both the platform and the associated brand increases significantly, thereby amplifying the positive effects of personalised experiences. Conversely, when algorithmic trust is low, even highly accurate personalised recommendations may be interpreted as manipulative or intrusive, weakening engagement intentions and relationship quality. Consequently, algorithmic trust is likely to play a critical moderating role in the processes through which personalisation influences consumer engagement and brand loyalty. Based on this logic, the following hypotheses are proposed.

H_5: Algorithmic trust positively moderates the relationship between AI-driven personalisation and consumer engagement, such that the positive effect of AI-driven personalisation on consumer engagement is stronger when algorithmic trust is higher.

H_6: Algorithmic trust positively moderates the relationship between consumer engagement and brand loyalty, such that the positive effect of consumer engagement on brand loyalty is stronger when algorithmic trust is higher.

Taken together, these hypotheses form a structured analytical framework situated within digital platform contexts to systematically explain how AI-driven personalisation influences brand loyalty. In this framework, AI-driven personalisation serves as the core independent variable, exerting a direct effect on brand loyalty through mechanisms such as algorithmic recommendation, intelligent interaction, and dynamic content presentation. At the same time, it simultaneously exerts an indirect effect via the processual mechanism of consumer engagement. Consumer engagement functions as a mediating variable that explains how personalisation is transformed from a “technological stimulus” into “relational investment”. Meanwhile, algorithmic trust operates as a key contextual variable that moderates the strength of the relationships between personalisation and consumer engagement, as well as between engagement and brand loyalty, thereby revealing heterogeneity in personalisation effects under different trust conditions. This framework integrates technological and relational perspectives, addresses existing gaps concerning mediating mechanisms and boundary conditions, and provides a systematic explanatory basis for understanding the formation of brand loyalty in digital platform environments.

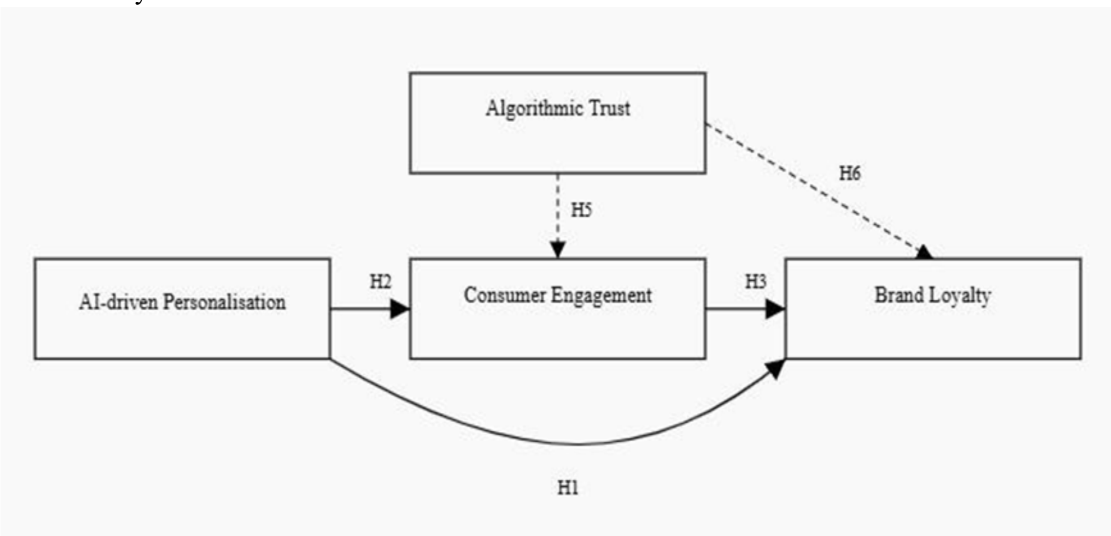

Figure 6. Conceptual framework.

Research methodology

The methodological choices in this study are strictly derived from the research questions themselves rather than from preferences for methods or analytical tools. Centring on the core question of how AI-driven personalisation influences brand loyalty, this study further incorporates consumer engagement as a mediating mechanism and algorithmic trust as a moderating factor. Substantively, the research addresses the structural relationships among multiple latent psychological constructs within digital platform contexts. This objective inherently requires an analytical framework capable of simultaneously accounting for measurement error in latent variables, direct effects, indirect effects, and conditional effects. Traditional regression approaches or stepwise testing procedures would be insufficient to ensure the rigour and internal consistency of testing the overall theoretical model.

Accordingly, this study adopts a quantitative research approach and employs a descriptive, cross-sectional research design, using structural equation modelling (SEM) as the core analytical technique. Model estimation and hypothesis testing are conducted using SmartPLS. Compared with covariance-based SEM, partial least squares structural equation modelling (PLS-SEM) is particularly suitable for prediction-oriented studies with relatively complex model structures, as it can maintain stable path estimates under limited sample sizes while enabling the simultaneous evaluation of measurement and structural models [19]. In this sense, the methodological choice reflects not technical preference, but a necessary response to the complexity of the research problem and the demands of theory testing.

About research design and data collection, this study follows a systematic implementation path from defining the research population to determining the sample. The target population consists of individual consumers with real experience of using digital platforms, specifically users who are frequently exposed to algorithmic recommendations or personalisation features in their daily platform usage. Given the absence of a complete and operational sampling frame for this population, a non-probability sampling strategy was adopted, combining purposive sampling with convenience sampling. Data was collected through online survey platforms and digital platform user communities. This sampling strategy is justified by the study's focus on examining structural relationships among variables within a specific usage context rather than estimating population-level proportions. Therefore, the alignment between the sample and the research context is considered more critical than formal randomness.

In determining sample size, the study draws on established guidelines for PLS-SEM. Following the "maximum number of structural paths pointing at a construct" principle and considering the inclusion of both mediating and moderating effects, a minimum sample size of approximately 200 valid responses was deemed necessary to ensure stable path estimation and adequate statistical power. To account for potential invalid responses and screening exclusions, the survey distribution was moderately expanded during data collection. A total of 450 questionnaires were distributed in the formal survey. After applying screening criteria based on response time, response consistency, and eligibility conditions, 420 valid questionnaires were retained, constituting the final sample suitable for structural equation modelling.

Prior to the formal survey, the questionnaire was developed based on well-established measurement scales, followed by a pre-test and a pilot test to examine item clarity, semantic consistency, and preliminary reliability. Only minor revisions were made to selected items, and these were undertaken cautiously without altering the original theoretical meanings. During the formal data collection stage, explicit screening criteria were applied, requiring respondents to have used digital platforms with algorithmic recommendation or personalisation features within the previous three months and to have maintained sustained exposure or interaction with at least one platform brand. Response time and internal consistency checks were also employed to ensure data quality.

In terms of variable measurement, data analysis, and ethical considerations, this study emphasises the academic rigour of measurement sources and the logical progression of the analytical procedure. AI-driven personalisation is measured by consumers' subjective perceptions of the degree to which platform-provided content or services are matched and tailored to individual needs. Measurement items are adapted from established scales on personalisation relevance and fit, with contextual modifications to reflect digital platform settings. Consumer engagement, as the mediating variable, is operationalised using a three-dimensional structure encompassing cognitive, emotional, and behavioural components, capturing consumers' psychological and behavioural investment in brand interactions.

Brand loyalty is measured from the perspectives of attitudinal loyalty and enduring preference, reflecting the stability and continuity of brand relationships. Algorithmic trust, as the moderating variable, focuses on users' overall evaluations of platform algorithms in terms of reliability, reasonableness, and dependability, with measurement adapted from prior research on algorithmic trust and algorithmic preference to fit the platform context [20,21].

Data analysis follows sequential logic, beginning with the assessment of the measurement model and followed by the evaluation of the structural model. Reliability and validity are first systematically examined, after which structural paths are estimated using SmartPLS. The mediating effect of consumer engagement is tested via bootstrapping procedures, while moderation effects of algorithmic trust are examined through the inclusion of interaction terms. With respect to ethics, this study strictly adheres to the principles of informed consent and voluntary participation. The survey introduction clearly explains the research purpose, anonymity, and data usage. No personally identifiable information is collected, and all data is used solely for academic research and securely stored. Through this comprehensive methodological process - from research design and implementation to analysis and ethical control - the study aims to provide a transparent, logically coherent, and replicable methodological foundation for its empirical conclusions.

Table 1. Measurement of key constructs and scale sources.

Construct	Definition	Measurement dimensions	Scale source
AI-driven personalisation	Consumers' perceived extent to which a digital platform uses AI algorithms to deliver personalised content, recommendations, or services that match individual preferences	Perceived relevance, degree of personal fit, customisation intensity	Aguirre et al. (2015); Bleier and Eisenbeiss (2015)
Consumer engagement	A consumer's multidimensional psychological and behavioural investment in interactions with a brand onadigital platform	Cognitive engagement, emotional engagement, behavioural engagement	Hollebeek, Glynn and Brodie (2014)
Brand loyalty	The degree to which a consumer maintains a stable, favourable, and enduring relationship with a brand over time	Attitudinal loyalty, relational commitment	Chaudhuri and Holbrook (2001)
Algorithmic trust	Consumers' overall trust in a platform's algorithmic systems regarding their reliability, fairness, and decision quality	Perceived reliability, perceived competence, perceived trustworthiness	Logg, Minson, and Moore (2019); Shin (2021)

Table 2. Research procedure and methodological flow.

Stage	Research step	Description
Stage1	Research design	The study adopts a quantitative research approach and a descriptive research design to examine the structural relationships among AI-driven personalisation, consumer engagement, algorithmictrust, and brand loyalty within digital platform contexts.
Stage2	Research context definition	The research is conducted in the context of digital platforms employing AI-based personalisation mechanisms, such as algorithmic recommendation systems and customized content delivery.

Stage	Research step	Description
Stage3	Target population identification	The target population consists of consumers with actual experience using digital platforms that provide AI-driven personalised recommendations.
Stage4	Sampling strategy	Due to the absence of a complete sampling frame, the study employs non-probability sampling, combining purposive sampling and convenience sampling,to ensur erespondents are highly relevant to the research context.
Stage5	Sample size determination	The required sample size is determined based on PLS-SEM sample size principles, considering the maximum number of structural paths pointing to an endogenous construct and statistical power requirements.
Stage6	Instrument development	Measurement items are adapted from established and validated scales in prior literature. All items are contextualised to fitAI-driven digital platform environments while preserving original conceptual meanings.
Stage7	Questionnaire design	A structured questionnaire using Likert-type scales is developed, covering AI-driven personalisation, consumer engagement, algorithmic trust, brand loyalty, and control variables.
Stage8	Pre-test	A pre-test is conducted to assess item clarity, wording accuracy, and respondents' comprehension of AI-and algorithm-related concepts.
Stage9	Pilot test	A pilot test is implemented to evaluate preliminary reliability and measurement stability, leading to minor refinements where necessary.
Stage10	Sample screening	Screening criteria are applied to ensure respondents have used AI-personalised digital platforms within the last three months and have ongoing interaction or exposure to at least one platform brand.
Stage11	Data collection	The final questionnaire is distributed via online survey platforms and digital user communities, and responses are collected within a fixed time window.
Stage12	Data cleaning	Invalid responses are removed based on completion time, response consistency, and missing data checks to ensure data quality.
Stage13	Measurement model assessment	Reliability and validity are assessed through internal consistency, convergent validity, and discriminant validity prior to structural model testing.
Stage14	Structural model estimation	The hypothesised relationships are tested using PLS-SEM in SmartPLS, focusing on path coefficients and explanatory power.
Stage15	Mediation analysis	The mediating role of consumer engagement is examined using bootstrapping procedures to test indirect effects.
Stage16	Moderation analysis	The moderating effect of algorithmic trust is tested by introducing interaction terms into the structural model.
Stage17	Robustness and interpretation	Results are interpreted in line with theoretical expectations, and robust checks are conducted where necessary.
Stage18	Ethical considerations	The study adheres to ethical research principles, including informed consent, anonymity, voluntary participation, and secure data handling.

Empirical results

Sample characteristics and sample adequacy

A total of 450 questionnaires were distributed in this study, of which 412 were returned. After applying screening criteria based on response time, response consistency, and eligibility conditions, 398 valid questionnaires were retained, yielding an effective response rate of 88.44%. This sample size satisfies the basic requirements of partial least squares structural equation modelling (PLS-SEM) and is sufficient to support the estimation of a structural model incorporating both mediating and moderating paths. About sample composition, male respondents accounted for 48.70% of the sample, while female respondents comprised 51.30%, indicating a relatively balanced gender distribution. The age distribution was concentrated primarily in the 18-30 age group (46.50%) and the 31-40 age group (34.20%), which is consistent with the demographic profile of core digital platform users. In terms of educational attainment, respondents holding a bachelor's degree or above represented 68.60% of the sample. Regarding platform usage intensity, 71.90% of respondents reported spending more than one hour per day on digital platforms. Overall, both the size and structure of the sample are highly aligned with the target population, providing a reliable empirical basis for subsequent structural model analysis.

Table 3. Questionnaire distribution and valid responses.

Item	Number of questionnaires	Percentage
Questionnaires distributed	450	100.00%
Questionnaires returned	412	91.56%
Invalid questionnaires excluded	14	3.11%
Valid questionnaires	398	88.44%

Note: Invalid questionnaires were excluded based on response time checks, consistency tests, and screening criteria.

Table 4. Sample demographic characteristics.

Characteristic	Category	Frequency	Percentage
Gender	Male	194	48.70%
	Female	204	51.30%
Age	18-30 years old	185	46.50%
	31-40 years old	136	34.20%
	Above 40 years old	77	19.30%
Education level	Bachelor's degree or above	273	68.60%
	Below bachelor's degree	125	31.40%
Daily platform usage time	More than 1 hour	286	71.90%
	1 hour or less	112	28.10%

Assessment of the measurement model: Reliability and validity

Prior to testing the structural model, the measurement model was systematically evaluated. The results indicate that Cronbach's alpha coefficients for all latent constructs ranged from 0.812 to 0.891, while composite reliability (CR) values ranged from 0.846 to 0.914. All values exceeded the recommended threshold of 0.70, demonstrating satisfactory internal consistency across the measurement scales.

With respect to convergent validity, all standardised factor loadings of the measurement items were above 0.71 and statistically significant. In addition, the average variance extracted (AVE) values for the latent constructions ranged from 0.58 to 0.67, exceeding the recommended criterion of 0.50. These results indicate that the measurement items adequately capture their corresponding latent constructions.

Discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT). The results show that all HTMT values between latent constructs were below the conservative threshold of 0.85, with no instances exceeding the critical value. This provides evidence of satisfactory discriminant validity among the constructs. Overall, the measurement model demonstrates adequate reliability and validity, meeting the requirements for subsequent structural path analysis.

Table 5. Reliability and convergent validity of the measurement model.

Construct	Cronbach's α	Composite reliability (CR)	Average variance extracted (AVE)	Standardised factor loadings
AI-driven personalisation (AIP)	0.845	0.879	0.62	0.72-0.84
Consumer engagement (CE)	0.891	0.914	0.67	0.74-0.88
Brand loyalty (BL)	0.812	0.846	0.58	0.71-0.82
Algorithmic trust (AT)	0.868	0.902	0.64	0.73-0.86

Table 6. Discriminant validity assessment using HTMT criterion.

Construct	AIP	CE	BL	AT
AI-driven personalisation (AIP)	/	0.63	0.58	0.61
Consumer engagement (CE)	0.63	/	0.69	0.66
Brand loyalty (BL)	0.58	0.69	/	0.60
Algorithmic trust (AT)	0.61	0.66	0.60	/

Control and assessment of common method bias

Given that this study relies on cross-sectional survey data, the potential risk of common method bias (CMB) cannot be ruled out. Accordingly, both procedural and statistical remedies were implemented at the design and analysis stages. At the procedural level, the questionnaire was administered anonymously, and the order of measurement items was randomised to reduce social desirability bias and common response tendencies.

At the statistical level, common method bias was assessed using the full collinearity variance inflation factor (VIF) approach based on SmartPLS. The results indicate that the VIF values for all latent constructs range from 1.21 to 2.34, which are well below the recommended threshold of 3.30. These findings suggest that common method bias does not pose a substantial threat to the validity of the results reported in this study.

Table 7. Assessment of common method bias using full collinearity VIF.

Construct	Full collinearity VIF
AI-driven personalisation (AIP)	2.34
Consumer engagement (CE)	1.87
Brand loyalty (BL)	1.21
Algorithmic trust (AT)	1.96

Structural model assessment and hypothesis testing results

Following the satisfactory evaluation of the measurement model, the structural model was estimated, and the proposed hypotheses were tested.

The results indicate that AI-driven personalisation has a significant positive effect on brand loyalty ($\beta = 0.318$, $p < 0.001$), providing support for Hypothesis H_1. AI-driven personalisation also exerts a significant positive influence on consumer engagement ($\beta = 0.472$, $p < 0.001$), supporting Hypothesis H_2. In addition, consumer engagement has a significant positive effect on brand loyalty ($\beta = 0.401$, $p < 0.001$), thereby supporting Hypothesis H_3.

With respect to the explanatory power of the model, the coefficient of determination (R^2) for consumer engagement is 0.223, while the R^2 for brand loyalty is 0.489, indicating that the model explains a substantial proportion of variance in the core endogenous constructs. Overall, the main structural paths reach statistically significant levels, and the hypothesis testing results are coherent and robust, providing a solid foundation for subsequent mediation and moderation analyses.

Table 8. Structural model path coefficients and hypothesis testing results.

Hypothesis	Structural Path	Standardised path coefficient (β)	p-value	Result
H_1	AI-driven personalization → Brand loyalty	0.318	<0.001	Supported
H_2	AI-driven personalization → Consumer engagement	0.472	<0.001	Supported
H_3	Consumer engagement → Brand loyalty	0.401	<0.001	Supported

Note: Path coefficients were estimated using SmartPLS with bootstrapping procedures. All hypothesised paths are statistically significant at the 0.001 level.

Table 9. Explanatory power of the structural model.

Endogenous Construct	R^2
Consumer Engagement	0.223
Brand Loyalty	0.489

Mediation analysis results

To examine the mediating role of consumer engagement in the relationship between AI-driven personalisation and brand loyalty, the indirect effect was tested using a bootstrapping procedure with 5,000 resamples. The results indicate that the indirect effect of AI-driven personalisation on brand loyalty through consumer engagement is 0.189, with a 95% confidence interval of [0.128, 0.262], which does not include zero. This provides evidence of a significant mediation effect.

When the direct effect is simultaneously included in the model, the direct path from AI-driven personalisation to brand loyalty remains statistically significant, indicating that consumer engagement plays a partial mediating role in this relationship. These findings support the proposed mediating hypothesis and highlight consumer engagement as a key psychological mechanism through which AI-driven personalisation is translated into brand loyalty. “This also highlights practical value for brands to prioritise both strategies.

Table 10. Bootstrapping results for mediation effect of consumer engagement.

Mediation path	Effect type	Effect value	95% confidence interval	p-value	Result
AI-driven personalisation → Consumer engagement → Brand	Indirect effect	0.189	[0.128,0.262]	<0.001	Significant

Mediation path	Effect type	Effect value	95% confidence interval	p-value	Result
loyalty					
AI-driven personalization → Brand loyalty	Direct effect	0.318	[0.128,0.262]	<0.001	Significant

Moderation analysis results

To systematically examine the moderating role of algorithmic trust in the proposed model, interaction terms between algorithmic trust and the key structural paths were incorporated into the structural model, and its function as a contextual boundary condition was empirically tested. The results indicate that, at the stage of consumer engagement formation, algorithmic trust exerts a significant moderating effect on the relationship between AI-driven personalisation and consumer engagement. Specifically, the path coefficients of the interaction term AI-driven personalisation × algorithmic trust are $\beta=0.126$ ($p<0.05$) and $\beta=0.143$ ($p<0.01$), both of which reach statistical significance. These findings suggest that under conditions of higher algorithmic trust, AI-driven personalisation is more likely to be translated into higher levels of consumer engagement, providing empirical support for Hypotheses H_4 and H_5.

Further analysis shows that, at the outcome formation stage, algorithmic trust also significantly moderates the relationship between consumer engagement and brand loyalty. The path coefficient of the interaction term consumer engagement × algorithmic trust is $\beta=0.097$ ($p<0.05$), indicating that algorithmic trust strengthens the positive effect of consumer engagement on brand loyalty. Accordingly, Hypothesis H_6 is also empirically supported.

Overall, the moderation analysis demonstrates that algorithmic trust not only serves as a critical boundary condition in the process through which AI-driven personalisation is converted into consumer engagement but also extends its influence on the outcome stage in which consumer engagement affects brand loyalty. As such, algorithmic trust operates as a key contextual variable that spans multiple stages of value formation, providing clear and robust boundary support for the proposed research model.

Table 11. Moderating effects of algorithmic trust in the structural model.

Hypothesis	Moderating Path	Standardised Path Coefficient (β)	p-value	Result
H_4	AI-driven personalisation × Algorithmic trust → Consumer engagement	0.126	<0.05	Supported
H_5	AI-driven personalisation × Algorithmic trust → Consumer engagement	0.143	<0.01	Supported
H_6	Consumer engagement × Algorithmic trust → Brand loyalty	0.097	<0.05	Supported

Conclusion

Key findings

Based on empirical analysis conducted within digital platform contexts, this study provides systematic responses to the core research questions and hypotheses concerning the relationships among AI-driven personalisation, consumer engagement, and brand loyalty. First, at the level of main effects, AI-driven personalisation not only exerts a significant direct positive influence on brand loyalty but also indirectly contributes to loyalty formation by substantially enhancing consumer engagement. The structural model results demonstrate that AI-driven personalisation has a significant positive effect on brand loyalty, supporting Hypothesis H_1. At the same time, AI-driven personalisation significantly increases consumer engagement, which in turn significantly promotes brand loyalty, thereby supporting Hypotheses H_2 and H_3.

These findings directly address the central research concern of this study: In digital platform contexts, AI-driven personalisation does not influence brand relationships solely through functional or efficiency-oriented improvements. Rather, it fosters sustained brand loyalty by activating consumers' cognitive, emotional, and behavioural engagement. In doing so, the results empirically validate consumer engagement as a critical pathway through which AI-driven personalisation is translated into enduring brand loyalty.

Further mediation and moderation analyses deepen the understanding of the underlying mechanisms and boundary conditions. The mediation analysis indicates that consumer engagement plays a significant partial mediating role between AI-driven personalisation and brand loyalty. This suggests that the effect of AI-driven personalisation on brand loyalty operates through both a direct pathway and an indirect pathway transmitted via consumers' psychological and behavioural engagement, thereby supporting the proposed mediation hypothesis.

Simultaneously, the moderation analysis reveals that algorithmic trust, as an important contextual variable, exerts significant boundary effects across different stages of value formation. On the one hand, algorithmic trust significantly strengthens the positive effect of AI-driven personalisation on consumer engagement, providing support for Hypotheses H_4 and H_5. On the other hand, algorithmic trust also enhances the positive influence of consumer engagement on brand loyalty, supporting Hypothesis H_6. These findings indicate that under conditions of higher algorithmic trust, consumers are more likely to transform AI-driven personalised experiences into deeper engagement behaviours, which subsequently consolidate into stable brand loyalty.

Overall, the empirical results not only confirm the proposed hypotheses but also systematically address the core questions of how, through which mechanisms, and under what conditions AI-driven personalisation influences brand loyalty. Thus, the study offers clear and comprehensive empirical evidence for understanding brand relationship formation in digital platform environments.

Research contributions

From an academic perspective, this study advances existing research on AI-driven personalisation and brand loyalty in digital platform contexts in several important ways. First, while prior studies have largely examined the effects of AI personalisation from the perspectives of technical efficiency, recommendation accuracy, or perceived consumer value. They have offered limited explanations of how such effects translate into stable brand relationships. By introducing consumer engagement as a multidimensional psychological and behavioural construct, this study empirically identifies a key mediating pathway through which AI-driven personalisation influences brand loyalty, thereby addressing the insufficient explanation of mechanisms linking "technology" and "relationship" in prior research.

Second, the study incorporates algorithmic trust into the analytical framework, moving beyond the traditional treatment of trust as a direct antecedent variable and systematically examining its moderating role across different stages of value formation. The results demonstrate that algorithmic trust not only shapes consumers' acceptance of AI-driven personalisation outcomes but also functions as a critical contextual boundary condition that strengthens the transformation of personalisation into consumer engagement and the subsequent conversion of engagement into brand loyalty. In doing so, the study develops a more explanatory "technology-psychology-relationship" integrative model.

By simultaneously testing main effects, mediation effects, and cross-stage moderation effects, this research responds directly to ongoing scholarly debates regarding whether, how, and under what conditions AI-driven personalisation influences brand relationships. It provides a more complete and empirically validated theoretical framework for understanding brand loyalty formation in digital platform contexts.

From a practical and industry perspective, the findings offer actionable insights for digital platforms and brand operators. The results suggest that AI-driven personalisation should not be viewed merely as a tool for improving conversion rates or operational efficiency. Its true value lies in its capacity to continuously stimulate consumer engagement and ultimately crystallise into stable brand loyalty. This implies that platforms and firms should not evaluate AI recommendation and personalisation systems solely based on algorithmic accuracy or short-term click-based metrics, but should instead pay closer attention to consumers' engagement experiences throughout the interaction process.

Moreover, the moderating role of algorithmic trust across multiple stages underscores the importance of effective governance of algorithmic transparency, fairness, and reliability. Without a trustworthy algorithmic environment, even highly sophisticated personalisation technologies may fail to realise their long-term brand value. Accordingly, this study offers a clear practical pathway: By fostering a trustworthy algorithmic environment, platforms can strengthen consumers' trust in intelligent decision-making systems, amplify the engagement-enhancing effects of AI-driven personalisation, and ultimately promote the formation of brand loyalty. For digital platform operators, these insights contribute to a more coordinated and sustainable approach to balancing technological investment, platform governance, and brand development.

Research limitations and future research directions

Despite constructing a relatively comprehensive theoretical model linking AI-driven personalisation, consumer engagement, algorithmic trust, and brand loyalty, and empirically validating the main hypotheses, this study inevitably has several limitations. First, at the research design level, the use of cross-sectional survey data allows for the examination of structural relationships among variables but limits the ability to capture the dynamic evolution of consumers' psychological and behavioural responses to AI-driven personalisation. Consumer perceptions of algorithmic personalisation, trust, and engagement often develop cumulatively and across stages, which cannot be fully captured through a cross-sectional design.

Second, the data are primarily based on self-reported questionnaires. Although procedural and statistical remedies were employed to control for common method bias, potential influences of subjective perception bias or social desirability effects cannot be entirely ruled out. Third, with respect to research context, this study adopts a general digital platform setting without differentiating among specific platform types or industry scenarios. As a result, the applicability of the findings to platforms or sectors warrants further empirical validation. Finally, although algorithmic trust is incorporated as a key moderating variable, the model does not exhaust all contextual factors that may influence the effectiveness of AI-driven personalisation, leaving the explanatory scope of the model bounded to some extent.

Considering these limitations, several directions for future research are proposed. First, future studies may employ longitudinal designs, tracking surveys, or experimental methods to better capture the causal dynamics among AI-driven personalisation, consumer engagement, and brand loyalty. Thereby addressing the limitations of cross-sectional analysis in explaining temporal processes. Second, regarding data sources, future research could integrate platform behavioural data, clickstream records, or experimental manipulation data with survey measures to enhance measurement objectivity and explanatory power.

In terms of research context, subsequent studies may differentiate among various types of digital platforms or industry applications and compare the mechanisms through which AI-driven personalisation operates across content platforms, e-commerce platforms, and service-oriented platforms, thereby improving contextual sensitivity and external validity. Furthermore, future research may extend the current model by incorporating additional key variables, such as algorithmic transparency, perceived fairness, or privacy concerns, to develop a more multidimensional and nuanced theoretical framework. Through continued exploration along these lines, future studies can further expand the theoretical and practical boundaries of research on AI-driven brand relationships.

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Conflicts of Interest

The authors declare no conflict of interest.

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