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The Impact of AI-Driven Personalization in Digital Marketing on Brand Loyalty among Algerian Online Consumers: Examining the Mediating Role of Customer Engagement

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ABSTRACT

This study examines the impact of AI-driven personalization in digital marketing on brand loyalty among Algerian online consumers, aiming to determine whether customer engagement mediates this relationship. Using a quantitative approach, data was gathered from 400 consumers across diverse backgrounds via a structured online survey. The questionnaire measured variables related to AI-driven personalization, customer engagement, and brand loyalty. Descriptive and inferential statistical analyses, including multiple linear regression and mediation analysis using the PROCESS Macro Model 4 with bootstrap resampling, were conducted using IBM SPSS 27. Results indicate that AI-driven personalization has a significant impact on increased brand loyalty and customer engagement. Moreover, customer engagement partially mediates the personalization–loyalty relationship, with the indirect effect exceeding the direct effect. Demographic analysis revealed significant differences in brand loyalty according to gender and online shopping frequency, while no significant differences were found by age or educational level. The study confirms that AI-driven personalization fosters brand loyalty, particularly when it activates consumer cognitive, emotional, and behavioral engagement. These findings highlight the necessity of integrating AI personalization strategies with engagement-building initiatives in digital marketing practice. AI-driven personalization emerges not only as a marketing tool but also as a strategic lever for building sustainable brand loyalty. In conclusion, investing in personalized digital experiences is vital to strengthening brand loyalty and enhancing consumer-brand relationships in Algeria.

Keywords: AI-driven personalization, digital marketing, customer engagement, brand loyalty, Algerian online consumers, mediation analysis.

RÉSUMÉ

Cette étude examine l'impact de la personnalisation par intelligence artificielle dans le marketing digital sur la fidélité à la marque chez les consommateurs algériens en ligne, visant à déterminer si l'engagement client joue un rôle médiateur dans cette relation. En adoptant une approche quantitative, des données ont été recueillies auprès de 400 consommateurs issus de divers milieux à travers un questionnaire structuré diffusé en ligne. Le questionnaire mesurait des variables liées à la personnalisation par IA, à l'engagement client et à la fidélité à la marque. Des analyses statistiques descriptives et inférentielles, y compris des régressions linéaires multiples et une analyse de médiation via le macro PROCESS Modèle 4 avec rééchantillonnage bootstrap, ont été réalisées à l'aide de SPSS. Les résultats indiquent que la personnalisation par IA est significativement associée à une fidélité accrue à la marque et à un engagement client renforcé. Par ailleurs, l'engagement client médiatise partiellement la relation personnalisation–fidélité, l'effet indirect dépassant l'effet direct. L'analyse démographique a révélé des différences significatives dans la fidélité à la marque selon le genre et la fréquence d'achat en ligne, tandis qu'aucune différence significative n'a été observée selon l'âge ou le niveau d'éducation. L'étude confirme que la personnalisation par IA favorise la fidélité à la marque, notamment lorsqu'elle active l'engagement cognitif, émotionnel et comportemental des consommateurs. Ces résultats soulignent l'importance d'intégrer les stratégies de personnalisation par IA dans les pratiques de marketing digital. La personnalisation par IA émerge ainsi non seulement comme un outil marketing, mais aussi comme un levier stratégique pour construire une fidélité durable. En conclusion, investir dans des expériences digitales personnalisées est essentiel pour renforcer la fidélité à la marque et améliorer les relations consommateur-marque en Algérie.

Mots-clés : personnalisation par intelligence artificielle, marketing digital, engagement client, fidélité à la marque, consommateurs algériens en ligne, analyse de médiation.

ملخص

تدرس هذه الدراسة تأثير التخصيص القائم على الذكاء الاصطناعي في التسويق الرقمي على الولاء للعلامة التجارية لدى المستهلكين الجزائريين عبر الإنترنت، وتهدف إلى تحديد ما إذا كان تفاعل العملاء يلعب دورًا وسيطًا في هذه العلاقة. من خلال منهجية كمية، تم جمع البيانات من 400 مستهلك من خلفيات متنوعة عبر استبيان منظم تم توزيعه إلكترونيًا. قاس الاستبيان متغيرات تتعلق بالتخصيص القائم على الذكاء الاصطناعي، وتفاعل العملاء، والولاء للعلامة التجارية. تم إجراء تحليلات إحصائية وصفية واستنتاجية، بما في ذلك الانحدار الخطي المتعدد وتحليل الوساطة باستخدام ماكرو PROCESS النموذج 4 مع إعادة التعيين بطريقة Bootstrap، باستخدام برنامج SPSS. تشير النتائج إلى أن التخصيص القائم على الذكاء الاصطناعي يؤثر بشكل دال إحصائيًا على زيادة الولاء للعلامة التجارية وتعزيز تفاعل العملاء. كما أن تفاعل العملاء يتوسط جزئيًا العلاقة بين التخصيص والولاء، حيث يتجاوز التأثير غير المباشر التأثير المباشر. أظهر التحليل الديموغرافي وجود فروق دالة احصائيا في الولاء للعلامة التجارية حسب الجنس وتكرار التسوق عبر الإنترنت، بينما لم تُلاحظ فروق دالة احصائيا حسب العمر أو المستوى التعليمي. تؤكد الدراسة أن التخصيص بالذكاء الاصطناعي يعزز الولاء للعلامة التجارية، لا سيما عندما ينشّط التفاعل المعرفي والعاطفي والسلوكي للمستهلكين. تبرز النتائج ضرورة دمج استراتيجيات التخصيص بالذكاء الاصطناعي مع مبادرات تعزيز التفاعل في الممارسات التسويقية الرقمية. يظهر التخصيص بالذكاء الاصطناعي ليس فقط كأداة تسويقية، بل أيضًا كرافعة استراتيجية لبناء ولاء مستدام. وفي الختام، فإن الاستثمار في التجارب الرقمية المخصصة أمر ضروري لتعزيز الولاء للعلامة التجارية وتحسين العلاقات بين المستهلك والعلامة التجارية في الجزائر.

الكلمات المفتاحية: التخصيص القائم على الذكاء الاصطناعي، التسويق الرقمي، تفاعل العملاء، الولاء للعلامة التجارية، المستهلكون الجزائريون عبر الإنترنت، تحليل الوساطة

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LIST OF ABBREVIATIONS

Abbreviation	Full Term	Explanation
AI	Artificial Intelligence	Technologies that simulate human intelligence to analyze data and automate decisions
CE	Customer Engagement	Consumer’s cognitive, emotional, and behavioral involvement with a brand
CI	Confidence Interval	Range within which a parameter is expected to fall
CRM	Customer Relationship Management	Systems used to manage customer interactions and data
CTR	Click-Through Rate	Percentage of users who click on digital content
DV	Dependent Variable	Outcome variable being explained
GRP	Gross Rating Point	Metric used in traditional advertising
IV	Independent Variable	Variable that influences another variable
ML	Machine Learning	AI systems that learn from data and improve automatically
MV	Mediating Variable	Variable that explains the relationship between IV and DV
NLP	Natural Language Processing	AI that enables understanding of human language
OOH	Out-Of-Home Advertising	Advertising outside the home (billboards, etc.)
p-value	Probability Value	Indicates statistical

		significance of results
PROCESS	PROCESS Macro for SPSS	Tool used for mediation and moderation analysis
ROI	Return on Investment	Measure of profitability of an investment
SD	Standard Deviation	Measure of data dispersion around the mean
SPSS	Statistical Package for the Social Sciences	Software used for statistical data analysis
S-O-R	Stimulus–Organism–Response	Framework explaining how stimuli affect internal states and behavior
TAM	Technology Acceptance Model	Model explaining how users accept and use technology

INTRODUCTION

Context of the Study

The rapid expansion of digital technologies has fundamentally reshaped the landscape of marketing, consumer behavior, and brand management over the past two decades. In an increasingly connected world, brands are no longer competing solely on product quality or price but on the quality and relevance of the digital experiences they deliver to each individual consumer. The proliferation of social media platforms, mobile applications, and data-driven advertising ecosystems has created an unprecedented volume of consumer behavioral data, allowing organizations to leverage artificial intelligence to personalize their marketing communications at a scale and precision that was previously unimaginable.

Artificial intelligence has emerged as one of the most transformative forces in contemporary digital marketing. By enabling systems to analyze vast quantities of consumer data in real time, identify individual behavioral patterns, and automatically adapt the content, timing, and format of brand communications to the specific context of each consumer, AI-driven personalization has shifted marketing from a mass-broadcast paradigm to an individualized interaction model. This shift carries profound implications for the way consumers perceive, engage with, and develop loyalty toward the brands they encounter in their digital environments.

Within this broader transformation, consumer engagement has gained increasing attention as a central construct mediating the relationship between marketing inputs and long-term brand outcomes. Consumers who actively process, emotionally connect with, and behaviorally respond to brand communications are significantly more likely to develop lasting loyalty relationships, characterized not merely by habitual repurchase but by a genuine psychological commitment to and advocacy for the brand. Understanding the mechanisms through which AI-driven personalization activates consumer engagement and, through it, brand loyalty has therefore become one of the most pressing questions in digital marketing research.

Algeria represents a particularly significant and yet understudied context for investigating these dynamics. As one of the most populous nations in Africa and the Arab world, with a population of 47.1 million and a rapidly growing digital consumer base of 36.2 million internet users as of early 2025, Algeria occupies a pivotal position in the emerging digital economy of the African continent (DataReportal, 2025).

Despite this digital dynamism, the Algerian e-commerce and digital marketing landscape is characterized by specific structural features that distinguish it from more mature Western or East Asian digital markets. Consumer trust in online transactions remains limited, with approximately 90% of online purchases settled through cash on delivery rather than electronic payment, reflecting persistent skepticism toward digital data exchange (UNCTAD, 2025). Brand trust, perceived transparency, and the quality of personalized consumer-brand interactions are consequently particularly decisive variables in the Algerian digital marketing context, making it an especially productive setting for investigating the mechanisms through which AI-driven personalization influences consumer engagement and brand loyalty.

This study is based on three main constructs. The first is AI-driven personalization, defined as the use of artificial intelligence technologies to provide personalized content, recommendations, and communications according to consumers' preferences and behaviors (Dwivedi et al., 2023). It represents the independent variable and is measured through perceived relevance, recommendation accuracy, and perceived usefulness.

The second construct is customer engagement, defined as the psychological state resulting from interactive consumer experiences with a brand (Brodie et al., 2011). It serves as the mediating variable and includes cognitive, emotional, and behavioral engagement.

The third construct is brand loyalty, defined as the consumer's long-term commitment to repurchase and remain attached to a preferred brand despite competing influences (Oliver, 1999). It represents the dependent variable and is measured through attitudinal loyalty and behavioral loyalty.

Problem Statement

The growing deployment of AI-driven personalization in digital marketing by companies targeting Algerian consumers stands in sharp contrast to the near-total absence of empirical research examining the consumer-behavior effects of these strategies in this specific national context. The international literature on AI personalization, consumer engagement, and brand loyalty is rich and growing, but it is overwhelmingly concentrated in Western and East Asian markets, with very few studies addressing the Arab world and none focusing specifically on the Algerian digital consumer. This geographic gap means that the relationships documented in the international literature cannot be assumed to hold in Algeria without empirical verification, given the distinctive trust dynamics, social media usage patterns, and consumer-brand relationship norms that characterize the Algerian market.

At the conceptual level, a further gap exists in the form of the mediation mechanism. While individual studies have examined the direct effect of AI personalization on brand loyalty, the direct effect of AI personalization on consumer engagement, and the direct effect of consumer engagement on brand loyalty, very few studies have simultaneously tested all three relationships within a single integrated mediation framework, and none have done so in the Algerian context. The role of consumer engagement as the mechanism through which AI personalization produces its effects on brand loyalty therefore remains empirically underexplored, leaving an important conceptual gap in the field.

At the practical level, the rapid growth of the Algerian digital consumer market and the increasing adoption of AI-driven marketing tools by companies operating in this market create an urgent need for evidence-based knowledge about what works, for whom, and through what mechanism in the Algerian digital marketing environment. In the absence of such knowledge, marketing decisions remain guided by frameworks developed in entirely different consumer contexts, with uncertain transferability.

Drawing on the opportunities and challenges identified in the existing literature regarding AI-driven personalization, customer engagement, and brand loyalty, this study is guided by the following main research question:

To what extent does AI-driven personalization in digital marketing affect brand loyalty among Algerian online consumers, and does customer engagement mediate this relationship?

Sub-Questions

This main question generates the following subsidiary research questions, each aligned with a specific variable relationship or dimension of the study:

SQ1. Does AI-driven personalization in digital marketing have a positive and significant effect on brand loyalty among Algerian online consumers?

SQ2. Does AI-driven personalization in digital marketing have a positive and significant effect on customer engagement among Algerian online consumers?

SQ3. Does customer engagement have a positive and significant effect on brand loyalty among Algerian online consumers?

SQ4. Does customer engagement mediate the relationship between AI-driven personalization and brand loyalty among Algerian online consumers?

SQ5. Does the relationship between AI-driven personalization and brand loyalty differ according to the socio-demographic characteristics and behavioral profile of Algerian online consumers, namely age, gender, online shopping frequency, and educational level?

Objectives of the Study

- **Objectives**

The general objective of this study is to empirically investigate the impact of AI-driven personalization in digital marketing on brand loyalty among Algerian online consumers, and to examine the mediating role of customer engagement in this relationship, with a view to generating theoretically and practically relevant knowledge for researchers and Algerian Online Consumers.

- **Specific Objectives**

The following specific objectives guide the empirical investigation and correspond directly to the sub-questions and hypotheses formulated above:

To measure the effect of AI-driven personalization on brand loyalty among Algerian online consumers (aligned with H1 and SQ1).

To measure the effect of AI-driven personalization on customer engagement among Algerian online consumers (aligned with H2 and SQ2).

To measure the effect of customer engagement on brand loyalty among Algerian online consumers (aligned with H3 and SQ3).

To test whether customer engagement mediates the relationship between AI-driven personalization and brand loyalty among Algerian online consumers (aligned with H4 and SQ4).

To examine whether socio-demographic characteristics and behavioral profile of Algerian online consumers, specifically age, gender, online shopping frequency, and educational level, moderate the relationship between AI-driven personalization and brand loyalty (aligned with H5 and SQ5).

Significance of the Study

This study makes three distinct contributions to the existing body of academic literature. First, it addresses a significant geographic gap by providing the first empirical investigation of the AI personalization-engagement-loyalty relationship specifically in the Algerian digital consumer context. The findings generated by this study enable a direct comparison with results from Western and East Asian markets, contributing to a more globally representative body of evidence on AI-driven digital marketing effects.

Second, this study contributes conceptually by testing the full mediation model in which AI-driven personalization influences brand loyalty both directly and indirectly through consumer engagement within a single integrated research design. Most existing studies have examined these relationships separately; this study provides one of the few empirical tests of the complete pathway, contributing to the theoretical understanding of the mechanisms through which AI personalization produces its effects on loyalty.

Third, the study integrates two established theoretical frameworks the Technology Acceptance Model (Davis, 1989) and the Stimulus-Organism-Response framework (Mehrabian & Russell, 1974) in a novel theoretical architecture that explains both the perceptual acceptance mechanisms and the behavioral response pathway through which AI personalization affects consumer engagement and loyalty.

From a practical standpoint, this study generates directly actionable knowledge for organizations operating in the Algerian digital market. By identifying which specific dimensions of AI-driven personalization, namely perceived relevance, recommendation accuracy, and perceived usefulness, most strongly activate consumer engagement and brand loyalty, the study enables marketing managers to prioritize their personalization investments and calibrate their digital communication strategies accordingly.

The findings regarding socio-demographic differences and the behavioral profile in the personalization-loyalty relationship are particularly valuable for practitioners seeking to segment their Algerian consumer base and tailor their AI personalization strategies to the specific needs, preferences, and trust levels of different age groups, genders, educational profiles, and shopping frequency segments. The strategic recommendations derived from the study's empirical findings provide a practical roadmap for implementing AI personalization in a manner that builds sustainable brand loyalty in the Algerian context.

At the contextual level, this study contributes to the nascent but growing body of research on digital marketing and consumer behavior in Algeria. By examining how AI-driven personalization influences Algerian online consumers who are characterized by unique trust dynamics, mobile-first internet usage, and strong social-media-oriented interaction patterns with brands the study offers researchers and practitioners an empirical foundation for better understanding the Algerian digital consumer, thereby contributing to the development of digital marketing scholarship in North African and Arab world contexts.

This study adopts a positivist epistemological stance, grounded in the assumption that the relationships between AI-driven personalization, customer engagement, and brand loyalty have an objective existence that can be measured and analyzed independently of the researcher's interpretive framework. Consistent with this positioning, the study follows a deductive research approach, proceeding from the theoretical propositions and hypotheses derived from the literature reviewed in Chapter 1 to their empirical verification through statistical analysis.

The methodological choice is quantitative, operationalized through a cross-sectional online survey strategy. The data collection instrument is a structured questionnaire comprising 30 Likert-scale items distributed across the three main variables and their eight dimensions, preceded by three screening questions and four demographic items. The questionnaire was validated through face validity review by three academic experts and a pilot test with eight respondents before final online distribution. Data were collected from a convenience non-probability sample of 400 valid respondents drawn from the population of Algerian online consumers, reached through Instagram, Facebook, WhatsApp, and Messenger over a defined data collection period.

Data analysis was conducted using IBM SPSS Statistics version 27. The analytical sequence comprised descriptive statistics, internal consistency reliability testing using Cronbach's alpha, normality testing using the Kolmogorov-Smirnov test, Pearson correlation analysis, simple and multiple linear regression for hypotheses H1 through H3, mediation analysis using the Hayes' PROCESS Macro Model 4 (2022) four-step multiple regression procedure for H4, and group difference tests including independent samples t-test for H5b and Kruskal–Wallis test for H5a, H5c, and H5d.

Scope and Limitations of the Study

The study is geographically confined to the Algerian national context. All respondents are Algerian nationals who use the internet regularly and have previously interacted with personalized brand content online. While the findings contribute to the literature on AI-driven digital marketing in North Africa and the Arab world more broadly, they cannot be directly generalized to other national contexts without replication, given the distinctive digital infrastructure, consumer trust dynamics, and cultural characteristics of the Algerian market.

The study employs a non-probability convenience sampling method, which limits the statistical generalizability of the findings to the full population of Algerian online consumers and reduces the extent to which the results can be generalized beyond the studied context. While a sample of 400 respondents is adequate for the regression and mediation analyses applied in this study, it may not fully capture the diversity of the Algerian digital consumer population in terms of geographic distribution, socioeconomic status, and digital literacy level. The online recruitment strategy, relying on social media platforms and messaging applications, may have introduced a selection bias toward more digitally active and socially connected consumer segments.

The cross-sectional design of the study captures a snapshot of consumer perceptions and attitudes at a single point in time, which limits the ability to draw inferences about the causal dynamics and temporal evolution of the relationships between AI personalization, consumer engagement, and brand loyalty. A longitudinal design tracking the same respondents over multiple measurement points would provide stronger causal evidence but was not feasible within the resources and timeline of this master's thesis research. Additionally, as the study relies on self-reported perceptual measures, it is subject to the common method bias that characterizes single-source survey-based research, though this limitation is partially mitigated by the validated measurement instruments and the robust sample size employed.

Research Outline

This thesis is organized into three chapters, each corresponding to a distinct phase of the research process. Chapter 1 develops the theoretical framework of the study through two sections: Section

1 presents a systematic literature review of the key relationships between AI-driven personalization, customer engagement, and brand loyalty, including Algerian contextual studies, and concludes with the identification of the research gaps that motivate this study; Section 2 develops the conceptual framework by defining the study's key constructs, theorizing the relationships between variables, presenting the theoretical models underpinning the research design, formulating the research hypotheses, and proposing the conceptual model that guides the empirical investigation.

Chapter 2 presents the methodological and contextual framework. Section 1 provides a contextual overview of the Algerian digital consumer environment through a field survey of current statistics on internet penetration, social media usage, and e-commerce behavior. Section 2 details the methodological framework, covering the research design, data collection method and instrument, population and sampling design, validity and reliability of the measurement instrument, and the data processing and statistical analysis procedures applied to test the study's hypotheses.

Chapter 3 presents the empirical results and their discussion. Section 1 reports the statistical results of all hypothesis tests in sequence, from descriptive statistics and reliability analysis through to regression, mediation, and group difference tests. Section 2 interprets and discusses these results in relation to the existing literature and the Algerian contextual specificities. The thesis concludes with a summary of the main findings, answers to the research hypotheses.

CHAPTER I : THEORETICAL FRAMEWORK

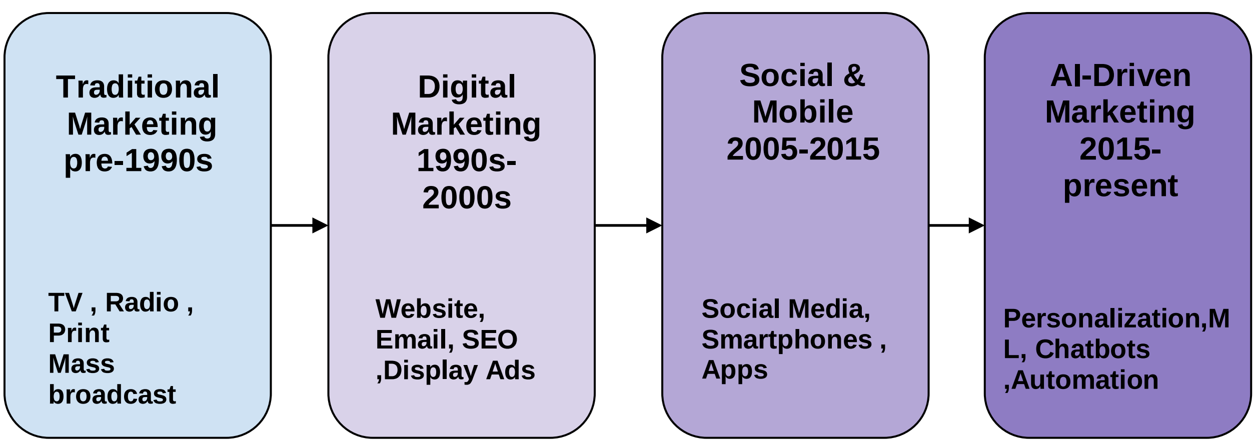
This chapter aims to establish the theoretical foundation of the study. It is divided into two sections. The first section presents a literature review on AI-driven personalization, customer engagement, and brand loyalty, while highlighting the relationships between these variables and identifying the main research gaps addressed by this study. The second section develops the conceptual framework by defining the key concepts of the research, explaining the theoretical relationships between the variables, presenting the theoretical models supporting the study, and formulating the research hypotheses.

Section 1: Literature Review

1. Digital Marketing Transformation and AI Integration

The past three decades have witnessed a fundamental transformation in how organizations communicate with and engage their consumers. Marketing has evolved from a discipline rooted in mass communication through traditional channels such as television, radio, and print media, to one increasingly defined by digital technology, data intelligence, and real-time interaction. This evolution unfolded progressively across four distinct phases, each building on the capabilities and limitations of the previous one (Vinerean & Opreana, 2024). Figure 1 below illustrates this progression from traditional marketing to the current AI-driven phase.

Figure 1: Evolution of Marketing Approaches



Source: Developed by ourselves based on (Vinerean & Opreana, 2024); (Hicham, 2023); (Dwivedi et al. 2023)

The emergence of the internet in the 1990s first enabled direct digital communication between brands and consumers. The rise of social media and smartphones from the mid-2000s onward gave consumers an active voice and created new touchpoints for brand interaction, while generating vast streams of behavioral data that marketers could draw upon to target and personalize communications (Lemon & Verhoef, 2016). The most significant development in this trajectory is the integration of artificial intelligence, which has transformed digital marketing from a reactive to a proactive discipline. Rather than interpreting past behavior to design future campaigns, AI systems analyze behavioral data in real time, predict individual consumer needs before they are expressed, and deliver personalized experiences automatically at scale (Hicham, 2023).

(Dwivedi et al., 2023) describe AI-driven personalization as the automated process through which digital systems use consumer data to create and deliver experiences that are uniquely relevant to each individual in real time and at scale. This definition captures the three properties that distinguish AI personalization from earlier forms of marketing customization: it is automated rather than human-driven, it operates in real time rather than in campaign cycles, and it functions at the individual level rather than the segment level. Table 1 below compares traditional and AI-driven marketing approaches across seven key dimensions.

Table 1 Traditional Marketing vs AI-Driven Marketing

Dimension	**Traditional Marketing**	**AI-Driven Marketing**
Targeting	Mass audience segments	Individual-level, data-driven
Personalization	NOne or segment-based	Real-time, one-to-one
Decision making	Human analysts, slow	Automated, real-time
Measurability	Difficult (reach, GRP)	Precise(CTR,ROI, conversion)
Consumer interaction	One-way broadcast	Two-way, conversational
Cost Efficiency	High cost per contact	Optimized per outcome
Tools	TV, radio, print, OOH	ML, NLP, chatbots, retargeting

Source: Developed by ourselves based on (Vinerean & Opreana, 2024); (Ahmed et al. 2025)

2. AI-Driven Personalization and Customer Engagement

The relationship between AI-driven personalization and customer engagement has attracted substantial scholarly attention, and the accumulated empirical evidence consistently documents a positive and significant effect of personalization on consumer engagement across its cognitive, emotional, and behavioral dimensions. Customer engagement is defined as a psychological state that occurs by virtue of interactive, co-creative consumer experiences with a brand within specific service relationships (Brodie, Hollebeek, Juric, & Ilic, 2011). It encompasses three mutually reinforcing dimensions: cognitive engagement, which refers to the consumer's mental processing of and attention to brand-generated content; emotional engagement, which refers to the positive affect and enthusiasm generated by brand interactions; and behavioral engagement, which encompasses observable actions such as liking, sharing, commenting, clicking, and purchasing.

(Hollebeek & Macky, 2019) demonstrated that content personalization is among the most powerful antecedents of all three engagement dimensions. Their study showed that consumers who perceive digital content as specifically tailored to their interests and behaviors are significantly more likely to invest cognitive, emotional, and behavioral resources in brand interactions than those receiving generic content. This three-dimensional engagement response is precisely what AI-driven personalization systems are designed to activate: by delivering content that is individually relevant, AI personalization increases the probability that consumers will attend to, respond to, and act upon brand communications.

(Dwivedi et al., 2023) applied the Stimulus-Organism-Response (S-O-R) framework to this relationship in a social media context and provided compelling empirical evidence. In their study, AI-driven personalization functioned as a stimulus that activated organism-level responses including perceived trust, perceived usefulness, and content relevance, which in turn generated behavioral engagement outcomes including liking, sharing, and commenting. Their quantitative study, conducted across multiple consumer populations, confirmed that the more accurately personalization systems match content to individual consumer profiles, the more deeply engaged those consumers become with the brand. This S-O-R mechanism provides the theoretical architecture for H2 of the present study.

(Vinerean & Opreana, 2024) identified the four AI capabilities that most significantly drive consumer engagement: personalized product recommendations based on behavioral history, real-time behavioral targeting in digital advertising, AI-augmented CRM systems enabling individualized follow-up communications, and conversational AI tools providing immediate personalized support. (Harmeling, Moffett, Arnold, & Carlson, 2017) theorized that AI-driven personalization catalyzes three forms of consumer investment: task-based engagement, experiential engagement, and social engagement, each contributing to deeper and more durable brand-consumer relationships. (Lim et al., 2025) identified hyper-personalization as the single most impactful lever of consumer engagement in contemporary digital marketing environments.

(Steinhoff, Arli, Weaven, & Kozlenkova, 2023) provided field-experimental confirmation, demonstrating that personalized social media content drives significantly higher cognitive and behavioral engagement than non-personalized content, with this engagement subsequently generating positive word-of-mouth and loyalty outcomes. (Bag et al., 2022) demonstrated, using the S-O-R framework, that AI-generated stimuli consistently activate stronger engagement responses than non-AI marketing inputs. (Ameen, Tarhini, Reppel, & Anand, 2021) found that personalized AI interactions generate particularly strong engagement among digitally literate consumers, a profile that characterizes a large and growing portion of the Algerian online population (Hima, Benarous, Louail, & Hamadi, 2024).

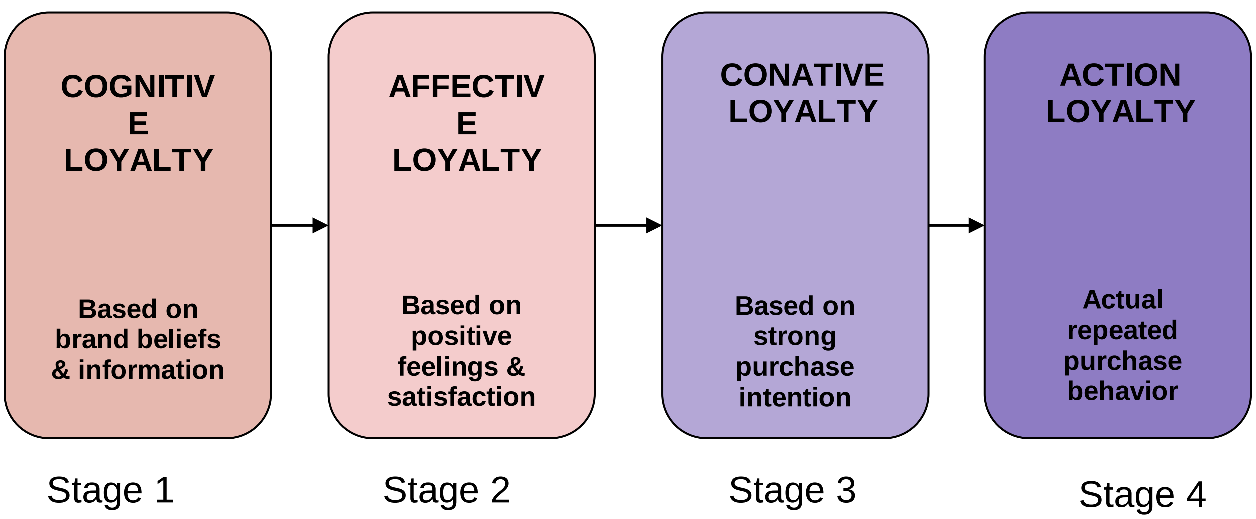
In the Algerian context specifically, (Hima et al., 2024) confirmed that Instagram is the primary channel through which personalized content reaches and engages young Algerian consumers, with personalized content generating significantly stronger engagement responses than generic brand communications. (Maamri, Djedid, & Tamma, 2024) found that Algerian digital consumers respond especially positively to personalized communications, with perceived personalization strongly associated with higher engagement levels and purchase intentions. These findings from the Algerian context provide direct contextual grounding for the research population of this study.

3. Customer Engagement and Brand Loyalty

The relationship between customer engagement and brand loyalty is among the most consistently and extensively documented in the marketing literature. Across methodologies, sectors, and consumer populations, the evidence converges on a robust positive relationship: consumers who invest cognitively, emotionally, and behaviorally in their interactions with a brand are substantially more likely to exhibit loyalty behaviors than those who remain disengaged. (Hollebeek, Glynn, & Brodie, 2022) demonstrated that engagement activates brand identification, which reinforces both attitudinal and behavioral loyalty. Their study showed that engagement is a critical bridge between marketing stimuli and loyalty outcomes including repurchase intention, advocacy, and resistance to switching.

(Brodie et al., 2011), whose foundational conceptualization of customer engagement anchors the literature, argued that engagement occupies a central position within the service ecosystem, functioning not merely as an outcome of marketing interactions but as a fundamental driver of loyalty, satisfaction, advocacy, and co-creation. Brand loyalty, as conceptualized by (Oliver, 1999), develops through four progressive stages, namely cognitive, affective, conative, and action loyalty, each representing a deeper level of consumer commitment. Consumer engagement, by generating positive brand experiences and strengthening emotional connection, accelerates movement through these stages, particularly the transition from cognitive to affective and from affective to conative loyalty. Figure 2 below illustrates Oliver's four-stage model.

Figure 2: Oliver's Four-Stage Brand Loyalty Model



Source: Developed by ourselves based on (Oliver, 1999); (Chaudhuri & Holbrook, 2001)

(Steinhoff et al., 2023) provided direct empirical evidence for the CE-loyalty link in the social media context. Their quantitative field study demonstrated that customer engagement is a strong and statistically significant predictor of customer loyalty, with the engagement-loyalty effect being particularly strong among consumers who had received personalized social media content. (Hollebeek & Macky, 2019) showed that engagement generates three key loyalty-relevant outcomes, namely brand trust, perceived value, and community identification, each of which independently reinforces loyalty across its attitudinal and behavioral dimensions.

(Kumar & Pansari, 2017) quantified the commercial significance of this relationship, estimating that increasing a customer from low to high engagement produces substantial gains in loyalty-related revenue and significant reductions in churn rates. Their study, conducted across multiple industries and consumer segments, identified engagement as one of the most powerful levers for building durable brand loyalty. (Changani & Kumar, 2024) confirmed that brand-generated social media engagement predicts brand loyalty in a mediated framework. (Al-Dmour, Alkhatib, Al-Dmour, & Amin, 2023) obtained analogous findings in the tourism sector, demonstrating that social media marketing activities drive brand loyalty both directly and indirectly through intermediate states including engagement.

(Vo et al., 2025) documented strong engagement-loyalty associations in the context of AI-generated social media content, showing that consumer engagement activated by AI-personalized content translates into measurable loyalty outcomes across both attitudinal and behavioral dimensions. (Lou & Xie, 2023) demonstrated that engagement mediates the relationship between digital content value and brand loyalty, with engagement fully mediating this relationship in some conditions and partially mediating it in others. In the Algerian context, (Telilani & Boutedja, 2024) found that personalized digital communications generate not only stronger engagement responses but also significantly higher loyalty intentions among Algerian consumers than generic outbound advertising. (Moulessehoul & Benabdelouahed, 2025) confirmed that consumer engagement with personalized social media content is the most effective predictor of brand loyalty among Algerian service-sector consumers.

4. AI-Driven Personalization and Brand Loyalty

The direct relationship between AI-driven personalization and brand loyalty constitutes one of the most actively studied topics in contemporary digital marketing research. A substantial and growing body of empirical work consistently demonstrates that AI personalization exerts a positive and significant direct effect on brand loyalty, operating through mechanisms including enhanced perceived value, increased brand trust, emotional resonance, and superior customer experience.

(Jiang & Wang, 2024) showed that personalization delivered through recommendation engines and behavioral data analytics significantly increases consumers' perceived value of brand interactions, which in turn strengthens their attitudinal commitment and behavioral loyalty. (Ahmed, Owais, Raza, Nadeem, & Ahmed, 2025) confirmed this finding through a quantitative survey, identifying perceived relevance and emotional resonance as the two primary mechanisms linking AI personalization to loyalty outcomes. They demonstrated that when AI systems deliver content that feels personally meaningful rather than generically targeted, consumers respond with increased trust, stronger brand attachment, and higher repurchase intentions. (Agbong-Coates & Aravindhan, 2025) validated these results across multiple sectors, showing that consumers exposed to higher levels of AI personalization consistently achieve superior scores on both attitudinal and behavioral loyalty measures.

(Gao, Liu, & Wu, 2023) demonstrated that personalized AI chatbot interactions enhance brand trust, which subsequently translates into brand loyalty. (Chen, Lu, Gong, & Xiong, 2023) extended this finding by showing that AI service quality, understood as the composite of personalization accuracy, response timeliness, and conversational smoothness, is a robust predictor of customer retention across service industries. (Chand et al., 2025) brought a customer journey perspective to this relationship, demonstrating that AI-personalized journeys spanning multiple digital touchpoints produce significantly stronger loyalty intentions than non-personalized ones. (Islam & Rahman, 2024) showed that predictive personalization, which anticipates consumer needs before they are expressed, achieves the highest loyalty outcomes of all personalization approaches.

(Ho & Chow, 2023) provided cross-cultural evidence from a non-Western market showing that AI-driven service interactions substantially improve brand preference and loyalty, reinforcing the expected applicability of these findings beyond Western contexts. (Broklyn, Olukemi, & Bell, 2024) identified an important boundary condition: the positive effect of AI personalization on brand loyalty holds only when consumers perceive the use of their data as ethical and transparent. When personalization is experienced as intrusive or opaque, it can generate reactance that erodes rather than reinforces loyalty. (Parris & Guzman, 2023) noted that brand loyalty has expanded beyond repurchase behavior to encompass active advocacy, co-creation, and community participation, all of which are facilitated by AI personalization systems that provide individualized opportunities for brand interaction.

5. Mediating Role of Customer Engagement

The mediating role of customer engagement between AI-driven personalization and brand loyalty constitutes the most integrative proposition of the research model. While the individual relationships reviewed in Sections 2 through 4 are each well documented, studies that simultaneously test all three relationships within a single mediation framework remain scarce, and the formal specification of customer engagement as a mediator between AI personalization and brand loyalty is an emerging area of inquiry.

(Shahzad, 2025) represents the most directly relevant precedent. Integrating both the TAM and S-O-R frameworks in a structural model, Shahzad demonstrated that customer engagement mediates the relationship between AI personalization and brand loyalty, providing direct conceptual precedent for H4. Their findings confirmed that the effect of AI personalization on loyalty is not exclusively direct but operates substantially through the intermediate mechanism of consumer engagement. (Ahmed et al., 2025) similarly found evidence of this mediation structure, showing that perceived relevance and engagement jointly mediate the path from AI personalization to loyalty outcomes.

(Bag et al., 2022), using the S-O-R framework, confirmed that engagement serves as a critical intermediate state between AI marketing inputs and downstream loyalty behaviors, operationalizing engagement as the organism-level response that converts personalization stimuli into loyalty outputs. (Lou & Xie, 2023) demonstrated that engagement mediates the relationship between digital content value and brand loyalty. (Al-Dmour et al., 2025) confirmed a parallel mediation structure in a developing market context, finding that intermediate psychological states including engagement mediate the pathway from marketing activities to brand loyalty outcomes, and noting that this pattern holds consistently across markets with varying levels of digital maturity.

The accumulation of evidence from these studies suggests that customer engagement is not merely a correlated variable but a genuine mechanism through which AI personalization produces its effects on brand loyalty. Personalization, by delivering individually relevant and valuable content, activates consumer cognitive processing, emotional connection, and behavioral participation. It is through this activated engagement that deeper and more durable brand loyalty is formed. Without engagement as the intermediate state, personalization may produce short-term behavioral responses but is unlikely to generate the attitudinal commitment and advocacy behaviors that characterize true brand loyalty as conceptualized by (Oliver, 1999).

6. Synthesis and Research Gap

The literature reviewed in Sections 1 through 5 converges on three confirmed findings that provide strong theoretical and empirical support for the study's hypotheses. First, AI-driven personalization consistently and positively influences brand loyalty, operating through perceived value, emotional resonance, and brand trust, across multiple sectors, contexts, and consumer populations (Jiang & Wang, 2024; Ahmed et al., 2025; Ho & Chow, 2023). Second, AI-driven personalization reliably activates customer engagement across its cognitive, emotional, and behavioral dimensions, with personalization quality being the decisive driver of this effect (Dwivedi et al., 2023; Vinerean & Opreana, 2024; Lim et al., 2025). Third, customer engagement consistently and significantly predicts brand loyalty, functioning as a critical mechanism that converts positive brand interactions into durable loyalty commitments (Hollebeek et al., 2022; Steinhoff et al., 2023; Brodie et al., 2011). Table 2 below synthesizes the key empirical studies reviewed in this section, their contexts, variables, and main findings.

Table 2 : Summary of Key Empirical Studies on AI Personalization, Engagement and Brand Loyalty

Authors & Year	**Context**	**Variables Studied**	**Key Finding**	**Algerian Context**
Jiang & Wang (2024)	E-commerce, china	AI personalization→ Brand loyalty	Personalization increases perceived value and attitudinal loyalty	No
Ahmed et al. (2025)	Online consumers, Pakistan	AI personalization→Engagement → Loyalty	Perceived relevance and emotional resonance drive loyalty via engagement	No
Dwivedi et al (2023)	Social media, Multi-country	AI personalization→ CE(S-O-R)	Personalization activates trust, relevance and behavioral engagement	No
Steinhoff et al. (2023)	Restaurant brand, Social media	CE→ Brand loyalty	Engagement significantly predicts loyalty; effect stronger with personalization	No
Shahzad (2025)	Digital marketing, Multiple sectors	AI→ CE→ Loyalty(Mediation)	CE mediates the AI-loyalty relationship	No

			within TAM-SOR model	
Hima et al. (2024)	Algerian university students	Social media → Purchase behavior	Instagram is main driver of Purchase intent among young Algerians	Yes
Maamri et al. (2024)	Algerian digital consumers	Digital marketing → Consumer behavior	Personalization strongly linked to brand preference in Algeria	Yes
Telilani & Boutedja (2024)	Algerian market	Inbound marketing → Consumer loyalty	Personalized digital comms more effective than outbound in Algeria	Yes

Source: Developed by ourselves based on reviewed literature

Despite this consistency, however, the literature also reveals three specific gaps that this study directly addresses. The first gap is geographic. The overwhelming majority of studies on AI personalization, engagement, and brand loyalty have been conducted in Western or East Asian markets. Algeria, with its distinctive digital consumer profile characterized by a predominantly young and mobile-first population, an Instagram and WhatsApp-dominant social media landscape, and high brand-trust sensitivity, remains almost entirely absent from this literature. The small number of existing Algerian studies (Maamri et al., 2024; Telilani & Boutedja, 2024; Hima et al., 2024; Moulessehoul & Benabdelouahed, 2025) have not tested the full AI personalization-engagement-loyalty mediation model, leaving a significant empirical void.

The second gap is conceptual. While the individual relationships between AI personalization and loyalty, between AI personalization and engagement, and between engagement and loyalty have each been studied in isolation, very few studies have simultaneously tested all three relationships within a single integrated mediation model. The mediating role of customer engagement between AI personalization and brand loyalty, formalized as H4 in this study, remains empirically underexplored, with most studies either testing direct effects only or examining engagement as a terminal dependent variable without connecting it to loyalty outcomes (Ahmed et al., 2025; Shahzad, 2025).

The third gap is practical. Despite the growing deployment of AI-driven digital marketing by companies targeting Algerian consumers, particularly in service sectors where personalized interaction is central to the consumer experience, no published study has examined the consumer-behavior effects of such strategies from the perspective of the actual audience of companies operating in this environment. This study addresses all three gaps by testing the full mediation model empirically on a sample of Algerian online consumers, contributing to the geographic, conceptual, and practical dimensions of the existing literature simultaneously. Table 3 below summarizes the three research gaps and this study's contribution to each.

Table 3: Research Gaps Addressed by This Study

Gap	**Nature**	**What is Missing**	**This study's Contribution**
Gap 1	Geographique	Most studies are Western or East Asian. Algerian consumers absent from AI personalization-loyalty research.	Tests the full model on Algerian online consumers via quantitative survey
Gap 2	Conceptual	AI personalization, CE and loyalty tested separately. No study integrates all three in one mediation model.	Examines the integrated relationships between variables and tests H1, H2, H3, and H4.
Gap 3	Practical	Limited research investigates AI-driven personalization effects within the context of e-commerce and online retail services in emerging markets like Algeria.	Explores the impact of AI-driven personalization on brand loyalty in Algerian online shopping environments

Source: Developed by ourselves

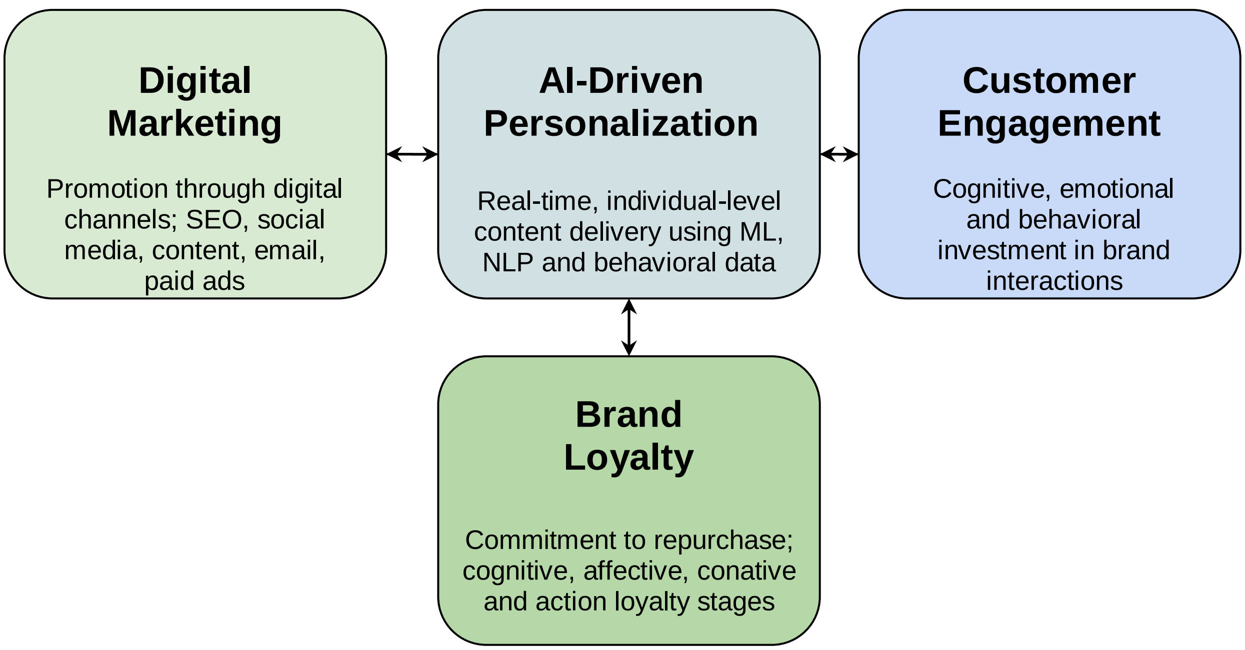
Section 2: Conceptual Framework

Building on the empirical review conducted in Section 1, Section 2 develops the conceptual architecture of this study. It defines the four core constructs, establishes the theoretical relationships between them, presents the theoretical frameworks that explain the mechanisms through which these relationships operate, and concludes with the proposed conceptual model and the four formal research hypotheses.

1. Key Concepts of the Study

The four core constructs of this study digital marketing, AI-driven personalization, customer engagement, and brand loyalty are distinct yet deeply interconnected. Understanding each concept clearly and precisely is essential before theorizing the relationships between them. Figure 3 below illustrates the four key concepts and the connections that link them.

Figure 3: Key Concepts of the Study and Their Interrelations



Source: Developed by ourselves based on reviewed literature

1.1 Digital Marketing

Digital marketing refers to the promotion of products and services through digital channels, including social media platforms, search engines, email, websites, and mobile applications. It emerged in the 1990s as an extension of traditional marketing into digital environments but has since evolved into a distinct discipline with its own methodologies, metrics, and strategic logic (Vinerean & Opreana, 2024). Unlike traditional marketing, which relies on mass broadcasting and limited consumer feedback, digital marketing is characterized by measurability, interactivity, and the capacity to target specific audiences based on behavioral, demographic, and psychographic data.

(Lemon & Verhoef, 2016) define digital marketing as the management of customer experience across digital touchpoints throughout the entire consumer journey, from awareness and consideration through purchase to post-purchase loyalty and advocacy. This journey-based conceptualization is particularly relevant to the present study because AI-driven personalization operates by customizing the content and timing of brand interactions at each touchpoint, shaping the cumulative consumer experience that determines engagement depth and loyalty strength.

The effectiveness of digital marketing is influenced by the strategic choices brands make regarding channel selection, content design, and personalization approach. Research consistently shows that digital marketing campaigns which leverage data-driven personalization significantly outperform generic mass-communication approaches on all major performance metrics including click-through rates, conversion rates, and consumer retention (Dwivedi et al., 2023). Digital marketing therefore serves as the broader operational context within which AI-driven personalization functions, providing the channels through which personalized content and communications are delivered to individual consumers.

1.2 AI-Driven Personalization: Definitions and Mechanisms

AI-driven personalization refers to the use of artificial intelligence technologies, including machine learning algorithms, natural language processing, predictive analytics, and behavioral data processing, to deliver individualized content, products, offers, and communications to each consumer based on their unique behavioral profile, preferences, and contextual signals (Dwivedi et al., 2023). It operates at the individual level rather than the segment level, updating consumer profiles continuously as new behavioral data becomes available and adapting marketing outputs in real time.

The literature distinguishes four progressive levels of personalization sophistication. Segment-based personalization targets groups sharing common characteristics. Behavioral personalization adapts content to individual browsing and purchase history. Predictive personalization anticipates future consumer needs based on pattern recognition. Hyper-personalization delivers real-time one-to-one experiences using live behavioral signals across all available data sources (Islam & Rahman, 2024; Lim et al., 2025). The effectiveness of AI personalization in generating engagement and loyalty outcomes increases significantly as the level of sophistication rises, with hyper-personalization producing the strongest effects across all outcome measures.

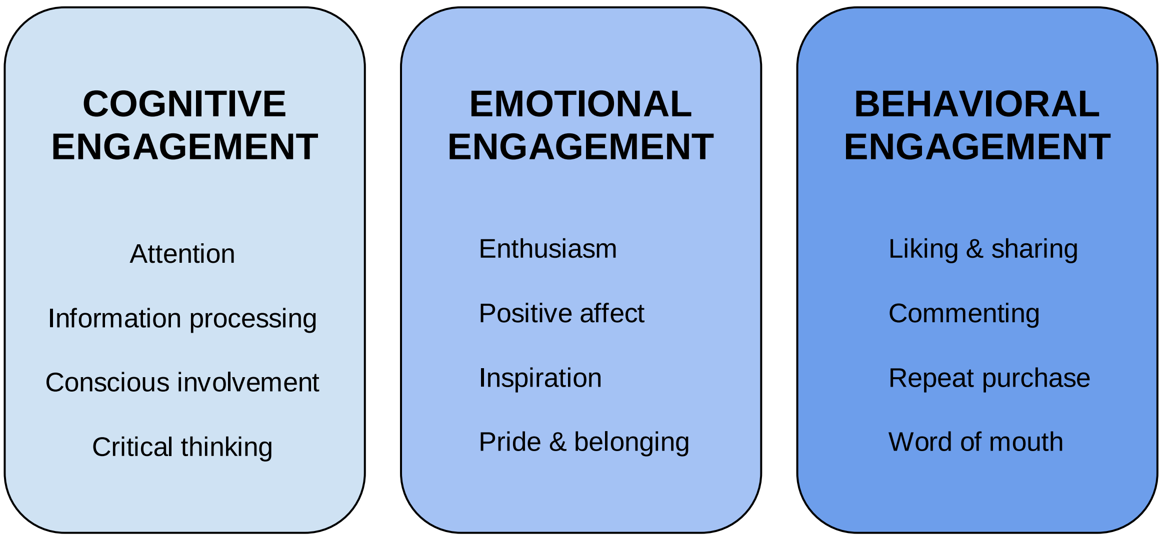
The mechanisms through which AI personalization operates include recommendation systems that analyze past consumer behavior to suggest relevant products or content, natural language processing tools that enable conversational and adaptive brand-consumer interactions, and behavioral retargeting systems that use data about past digital interactions to deliver targeted advertising across platforms (Vinerean & Opreana, 2024). Each of these mechanisms contributes to the central function of AI personalization: transforming anonymized mass communication into individualized, contextually appropriate consumer experiences that activate engagement and build loyalty over time.

1.3 Customer Engagement: Definitions and Dimensions

Customer engagement is defined as a psychological state that occurs by virtue of interactive, co-creative consumer experiences with a brand within specific service relationships (Brodie et al., 2011). It is fundamentally multidimensional, encompassing cognitive, emotional, and behavioral components that together capture the depth and quality of the consumer-brand relationship. Cognitive engagement refers to the consumer's attention to and intellectual processing of brand-generated content. Emotional engagement refers to the enthusiasm, positive affect, and sense of connection generated by brand interactions. Behavioral engagement encompasses observable actions including content liking, sharing, commenting, purchasing, and brand advocacy.

(Kumar & Pansari, 2017) operationalized customer engagement at the behavioral level through four dimensions that generate distinct forms of value for organizations: customer purchases, customer referrals, customer influence through social media, and customer knowledge sharing through feedback and co-creation. (Harmeling et al., 2017) further theorized that engagement marketing tools catalyze three forms of consumer investment task-based, experiential, and social engagement, each contributing to deeper brand-consumer relationships and stronger loyalty outcomes. Figure 4 below illustrates the three core dimensions of customer engagement.

Figure 4: The Three Dimensions of Customer Engagement



Source: Developed by ourselves based on (Brodie et al. 2011); (Harmeling et al. 2017); (Kumar & Pansari 2017)

In this study, customer engagement serves as the mediating variable that connects AI-driven personalization to brand loyalty. When AI personalization delivers content that is individually relevant and valuable, it activates the cognitive, emotional, and behavioral investment that constitutes customer engagement. This engagement, in turn, deepens the consumer's relationship with the brand and generates the trust, perceived value, and community identification that translate into brand loyalty over time (Hollebeek & Macky, 2019).

1.4 Brand Loyalty: Definitions and Dimensions

Brand loyalty is defined as a deeply held commitment to rebuy or repatronize a preferred product or service consistently in the future, despite situational influences and marketing efforts designed to induce switching behavior (Oliver, 1999). This definition captures both the attitudinal dimension of loyalty, which refers to the consumer's positive psychological commitment to the brand, and the behavioral dimension, which refers to the pattern of consistent repurchase. The integration of both dimensions distinguishes true loyalty from mere habitual repurchase driven by inertia or convenience.

(Oliver, 1999) described loyalty as developing through four progressive stages. Cognitive loyalty emerges first, based on information about the brand's performance relative to alternatives. Affective loyalty develops next as positive experiences generate favorable feelings and satisfaction. Conative loyalty reflects a strong intention to repurchase, representing deeper psychological commitment. Action loyalty manifests as actual repeated purchase behavior that persists even in the face of competitive alternatives. This four-stage model highlights that true loyalty is not simply a behavioral pattern but a psychological state cultivated through a sequence of positive brand experiences.

(Chaudhuri & Holbrook, 2001) demonstrated that brand trust and brand affect are the two most powerful antecedents of loyalty, predicting both its attitudinal and behavioral manifestations. Their research showed that trust is particularly important in service contexts where consumers cannot fully evaluate quality before purchase and must rely on brand reputation and prior interaction quality as signals of reliability. (Parris & Guzman, 2023) noted that the conceptualization of brand loyalty has progressively expanded to encompass not only repurchase behavior and attitudinal commitment but also active advocacy, co-creation of value, and community participation, representing higher-order expressions of loyalty that AI personalization facilitates through individualized brand interaction opportunities.

1.5 Challenges and Ethical Considerations of AI in Marketing

While AI-driven personalization offers significant marketing benefits, its deployment also raises important challenges and ethical considerations that constitute boundary conditions on the relationships studied in this research. The effectiveness of AI personalization is fundamentally dependent on the collection, storage, and processing of large volumes of consumer behavioral data. This data dependency creates significant privacy risks that can, if poorly managed, undermine the engagement and loyalty outcomes that personalization is designed to generate (Broklyn, Olukemi, & Bell, 2024).

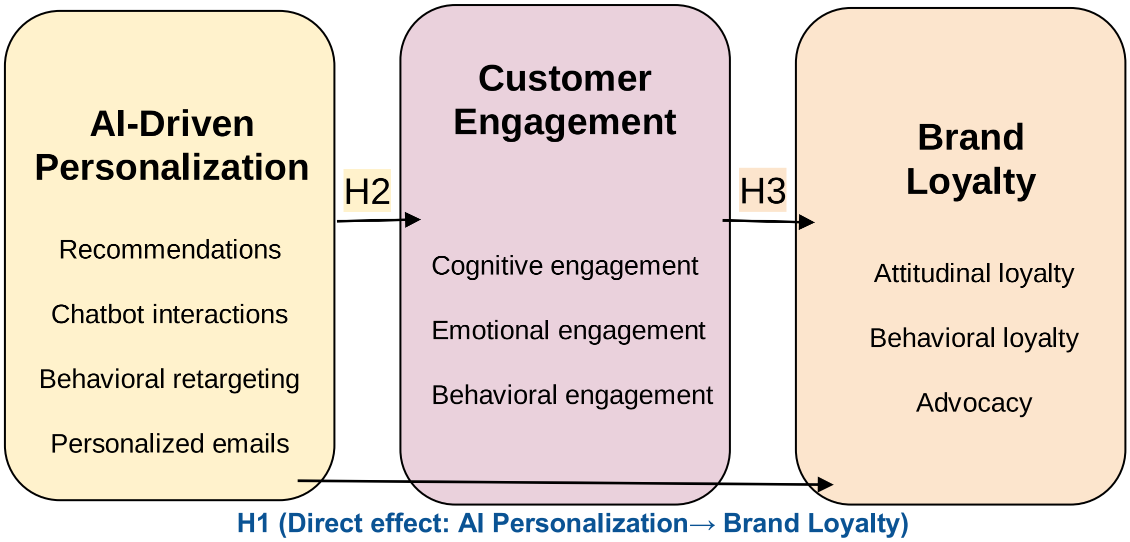
(Dwivedi et al., 2023) identified data privacy concerns as the most important moderator of the AI personalization-engagement relationship. Their study found that perceived privacy risk functions as a negative organism-level response that partially counteracts the positive engagement effects of personalization. When consumers believe that their personal data is being collected and used without their genuine consent, the trust damage generated can negate or even reverse the loyalty-building effects of personalization. (Ameen, Tarhini, Reppel, & Anand, 2021) examined the privacy calculus through which consumers navigate the tension between personalization benefits and privacy risks, finding that consumers accept personalization when its benefits are clear and risks feel manageable, but resist it when data practices feel opaque or intrusive.

Beyond data privacy, the deployment of AI in marketing raises ethical challenges related to algorithmic bias, the potential for consumer manipulation, and the creation of filter bubbles that limit consumer choice. Algorithmic bias occurs when AI systems trained on skewed historical data reproduce and amplify existing inequalities in their recommendations and targeting decisions. Filter bubbles, created when recommendation algorithms consistently show consumers content aligned with their past preferences, progressively narrow the consumer's information environment. Transparency is the overarching ethical requirement that addresses all of these concerns: when consumers understand what data is being used and have meaningful control over their personalization experience, the ethical risks of AI marketing are substantially reduced and its trust and loyalty benefits are enhanced (Broklyn et al., 2024).

2. Theoretical Relationships Between the Study Variables

The conceptual model of this study proposes four theoretical relationships between the study variables, each grounded in the empirical literature reviewed in Section 1 and each formalized as a testable hypothesis. Figure 5 below provides a visual overview of these relationships and their corresponding hypotheses.

Figure 5: Theoretical Relationships Between Study Variables



Source: Developed by ourselves

2.1 AI Personalization and Customer Engagement

The theoretical basis for H2 rests on the principle that perceived relevance is the primary driver of consumer engagement with brand-generated content. When AI systems deliver content that accurately reflects individual consumer preferences and needs, consumers perceive this content as personally meaningful rather than generically targeted. This perception of relevance activates the cognitive processing, emotional response, and behavioral action that define customer engagement (Hollebeek & Macky, 2019; Dwivedi et al., 2023). The more precisely personalization systems match content to individual profiles, the stronger the engagement activation. On the basis of this evidence, the study proposes H2: AI-driven personalization has a positive and significant effect on customer engagement.

2.2 Customer Engagement and Brand Loyalty

The theoretical basis for H3 rests on the established finding that the depth of consumer investment in brand interactions is a primary determinant of loyalty development. When consumers engage cognitively, emotionally, and behaviorally with a brand, they develop stronger brand identification, higher perceived value, and greater emotional attachment, all of which reinforce the attitudinal commitment and behavioral patterns that constitute brand loyalty

(Hollebeek et al., 2022; Brodie et al., 2011). Engagement functions as a mechanism through which marketing interactions are converted into lasting brand relationships. On the basis of this evidence, the study proposes H3: Customer engagement has a positive and significant effect on brand loyalty.

2.3 AI Personalization and Brand Loyalty (H1)

The theoretical basis for H1 rests on the finding that AI personalization enhances the quality and relevance of consumer-brand interactions, generating superior perceived value, increased brand trust, and stronger emotional resonance than non-personalized interactions. These outcomes independently and collectively reinforce the attitudinal commitment and behavioral intentions that characterize brand loyalty (Jiang & Wang, 2024; Ahmed et al., 2025; Agbong-Coates & Aravindhan, 2025). This direct effect operates partly independently of and partly through the mechanism of customer engagement. On the basis of this evidence, the study proposes H1: AI-driven personalization has a positive and significant direct effect on brand loyalty.

2.4 Mediating Role of Customer Engagement (H4)

The theoretical basis for H4 rests on the S-O-R framework's account of how marketing stimuli produce behavioral responses through intermediate psychological states. AI personalization as the stimulus activates customer engagement as the organism-level response, which in turn generates brand loyalty as the behavioral output. When engagement is introduced into the model, the direct effect of AI personalization on loyalty may be partially reduced, indicating that engagement absorbs a significant portion of the personalization-loyalty pathway. On the basis of this evidence, the study proposes H4: Customer engagement mediates the relationship between AI-driven personalization and brand loyalty (Bag et al., 2022; Shahzad, 2025).

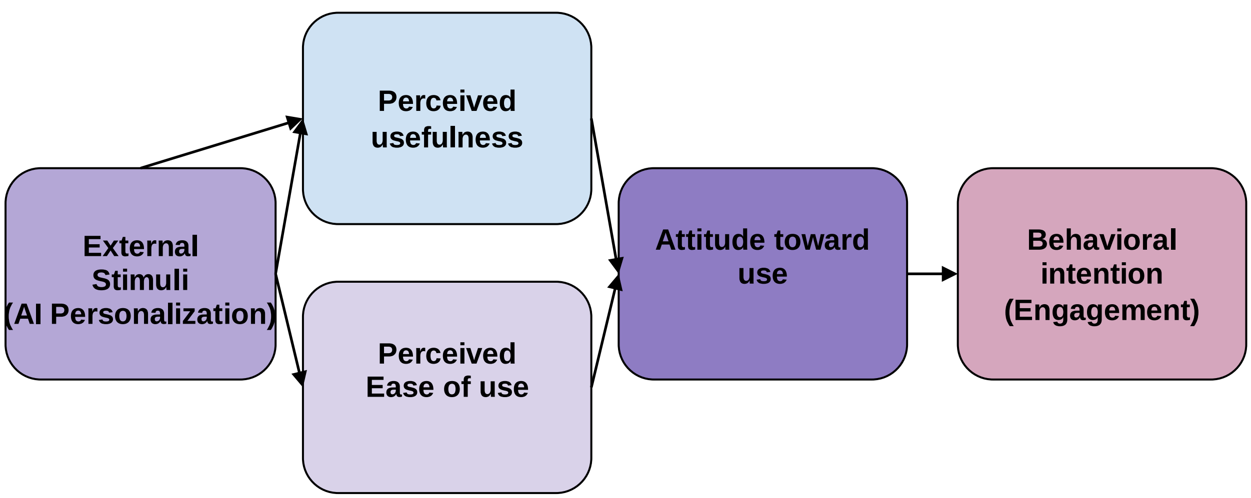
3. Theoretical Models Supporting the Framework

3.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), originally developed by Davis (1989), proposes that consumer adoption of a new technology is primarily determined by two perceptual beliefs: perceived usefulness, which refers to the degree to which an individual believes that using the technology will enhance their outcomes, and perceived ease of use, which refers to the degree to which an individual believes that using the technology requires minimal effort. These two beliefs shape attitude toward the technology, which in turn determines behavioral intention and actual use behavior.

In the marketing context, TAM explains why consumers come to accept and engage with AI-driven personalization systems. When consumers perceive AI-personalized content as useful, relevant, and non-intrusive, they develop a positive attitude toward the brand's use of AI personalization, which increases their likelihood of engaging with personalized content and remaining loyal to brands that deliver it. (Al-Ansi et al., 2024) confirmed in a comprehensive two-decade review of TAM research that perceived usefulness is the most consistent predictor of consumer attitude toward AI-driven marketing tools, and that this attitude subsequently predicts both engagement intention and loyalty behavior. (Ibrahim, Munscher, Daseking, & Telle, 2025) validated this specifically in the AI context, showing that perceived usefulness of AI personalization systems predicts engagement intention with high statistical significance (Beta = 0.34, $p < 0.001$). Figure 6 below illustrates the TAM model as applied to the AI marketing context.

Figure 6: Technology Acceptance Model Applied to AI-Driven Marketing



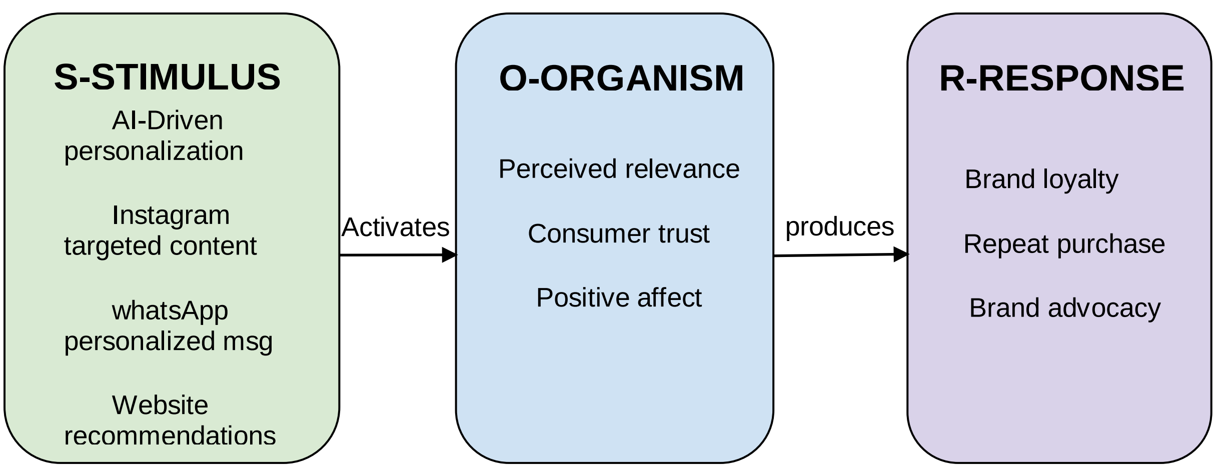
Source: Developed by ourselves based on (Davis, 1989); (Al-Ansi et al. 2024); (Ibrahim et al. 2025)

3.2 Stimulus-Organism-Response (S-O-R) Framework

The Stimulus-Organism-Response (S-O-R) framework, originally proposed by Mehrabian and Russell (1974) in environmental psychology, provides a sequential account of how environmental stimuli produce behavioral responses through intermediate psychological states. Stimuli from the environment activate internal psychological processes within the organism, which in turn generate behavioral responses. Applied to the present study, AI-driven personalization serves as the stimulus, customer engagement represents the organism's internal response, and brand loyalty is the behavioral outcome.

(Dwivedi et al., 2023) applied this framework to AI personalization on social media and confirmed that personalization activates organism-level responses including perceived trust and relevance, which subsequently generate behavioral engagement and purchase intention. (Bag et al., 2022) demonstrated that AI-generated stimuli activate stronger organism-level responses than non-AI marketing inputs. (Wang & Wu, 2024) integrated TAM and S-O-R frameworks and showed that the combined approach provides the most comprehensive explanation of how digital marketing stimuli produce engagement and loyalty outcomes. The S-O-R framework is particularly valuable for this study because it provides the theoretical rationale for the mediating role of customer engagement: as the organism-level construct, engagement is the psychological mechanism through which the personalization stimulus is converted into the loyalty behavioral response. Figure 7 illustrates the S-O-R framework as applied to this study.

Figure 7: The S-O-R Framework Applied to AI-Driven Personalization



Source: Developed by ourselves based on (Mehrabian & Russell, 1974); (Dwivedi et al. 2023); (Shahzad, 2025)

4. Proposed Conceptual Model

Drawing on the theoretical frameworks of the Technology Acceptance Model (TAM) and the Stimulus-Organism-Response Model (S-O-R), and grounded in the empirical literature reviewed in Section 1, this study proposes a conceptual model in which AI-driven personalization is positioned as the independent variable (IV), brand loyalty as the dependent variable (DV), and customer engagement as the mediating variable (MV). The model captures both the direct influence of AI-driven personalization on brand loyalty and the indirect influence operating through customer engagement. It also incorporates demographic characteristics age, gender, online shopping frequency, and educational level as moderating variables that may affect the strength of the relationship between personalization and brand loyalty across different consumer segments.

From the perspective of S-O-R theory, AI-driven personalization functions as the stimulus, customer engagement represents the organism's internal response, and brand loyalty constitutes the behavioral outcome. TAM complements this explanation by highlighting how consumers' perceptions of usefulness and trust contribute to the acceptance and appreciation of AI-driven personalization rather than perceiving it as intrusive. The model further assumes that consumer responses to personalized digital marketing vary according to demographic differences, suggesting that the effectiveness of AI-driven personalization may differ across consumer groups.

Based on the literature reviewed on AI-driven personalization, customer engagement, and brand loyalty, as well as the research questions formulated above, the following hypotheses are proposed to guide the empirical investigation:

Main Hypothesis:

> **H0:** AI-driven personalization in digital marketing has a significant effect on brand loyalty among Algerian online consumers through the mediating role of customer engagement.

Sub-Hypotheses:

H1: AI-driven personalization in digital marketing has a positive and significant effect on brand loyalty among Algerian online consumers.

H2: AI-driven personalization in digital marketing has a positive and significant effect on customer engagement among Algerian online consumers.

H3: Customer engagement has a positive and significant effect on brand loyalty among Algerian online consumers.

H4: Customer engagement mediates the relationship between AI-driven personalization in digital marketing and brand loyalty among Algerian online consumers.

H5: The relationship between AI-driven personalization and brand loyalty differs according to Algerian online consumers' socio-demographic characteristics and behavioral profile.

H5a: The relationship between AI-driven personalization and brand loyalty differs according to consumers' age.

H5b: The relationship between AI-driven personalization and brand loyalty differs according to consumers' gender.

H5c: The relationship between AI-driven personalization and brand loyalty differs according to consumers' online shopping frequency.

H5d: The relationship between AI-driven personalization and brand loyalty differs according to consumers' educational level.

Conclusion

This chapter provided the theoretical and conceptual foundation of the study by reviewing the major academic contributions related to AI-driven personalization, customer engagement, and brand loyalty in digital marketing environments. The literature review demonstrated that AI-driven personalization has become a strategic marketing tool capable of enhancing consumer experiences, stimulating engagement, and strengthening long-term loyalty toward brands. The reviewed studies also confirmed the existence of significant relationships between the three main variables and highlighted the important mediating role of customer engagement in transforming personalized digital experiences into sustainable loyalty outcomes.

The chapter also identified several gaps in the existing literature, particularly the limited number of studies conducted in the Algerian context and the scarcity of research integrating AI-driven personalization, customer engagement, and brand loyalty within a single mediation framework. To address these gaps, the conceptual framework of the study was developed based on the Technology Acceptance Model (TAM) and the Stimulus–Organism–Response (S-O-R) framework, which together provide a comprehensive explanation of how AI personalization influences consumer behavior and loyalty outcomes.

Overall, this chapter established the theoretical basis for the empirical investigation conducted in the following chapters by clarifying the study variables, the relationships between them, and the hypotheses to be tested.

CHAPTER II : METHODOLOGICAL AND CONTEXTUEL FRAMEWORK

This chapter aims to present the contextual and methodological framework of the study. It is divided into two sections. The first section provides an overview of the Algerian digital environment by examining internet usage, social media adoption, e-commerce behavior, and the profile of Algerian online consumers. The second section explains the methodological framework adopted in the study, including the research design, data collection method, questionnaire structure, sampling procedures, validity and reliability measures, and statistical analysis techniques used to test the research hypotheses.

Section 1: Contextual Framework

This section establishes the empirical context of the study by presenting a field-based overview of Algerian online consumer behavior. Drawing on recent data from international digital research institutes and specialized market intelligence platforms, it documents the current state of internet adoption, social media usage, e-commerce penetration, and key behavioral characteristics of Algerian digital consumers. This contextual grounding is essential for situating the study's research population within a concrete and measurable reality, and for justifying the relevance of investigating AI-driven personalization and brand loyalty within this specific national environment.

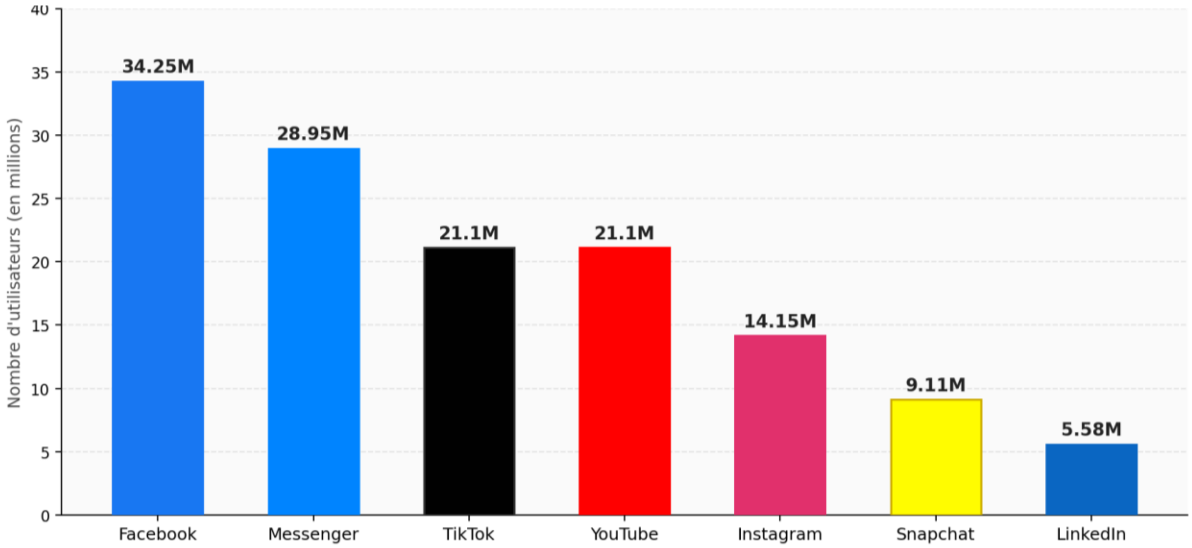
1. Internet Penetration and Digital Infrastructure in Algeria

Algeria has undergone rapid and sustained digital development over the past decade, establishing itself as one of the most significant internet markets on the African continent. According to the DataReportal Digital 2025 Report, 36.2 million Algerians were internet users at the start of 2025, representing a penetration rate of 76.9% of the total population of 47.1 million. This figure marks a notable increase compared to 33.49 million users recorded in early 2024 (72.9% penetration), confirming an accelerating trajectory of digital adoption . Mobile connectivity is the primary driver of this expansion. GSMA Intelligence data cited in the DataReportal 2025 report indicates that there were 54.8 million active mobile connections in Algeria at the start of 2025, equivalent to 116% of the total population, reflecting the widespread practice of holding multiple SIM cards. Furthermore, 91.4% of these mobile connections operate on broadband networks (3G, 4G, or 5G), confirming that the vast majority of Algerian internet access occurs through high-speed mobile networks (DataReportal, 2025). An UNCTAD assessment published in 2025 further confirms that mobile broadband coverage extends to over 98% of the Algerian population, and that Algeria offers the second most affordable mobile internet access in Africa (UNCTAD, 2025).

2. Social Media Usage and Platform Preferences

Social media occupies a central position in the digital lives of Algerian consumers. DataReportal (2025) reports that there were 25.6 million social media users aged 18 and above in Algeria at the start of 2025, equivalent to 54.2% of the total population and 83.5% of the adult population. This user base grew by 700,000 users (+2.8%) compared to early 2024, confirming a steady upward trend in social media adoption. Among these users, 58% are male and 42% are female, and 70.5% of all internet users in Algeria are active on at least one social media platform (DataReportal, 2025). In terms of platform distribution, Facebook remains the dominant social network in Algeria. NapoleonCat data cited in Statista (2025) indicates that Facebook had 34.25 million users in Algeria in December 2025, representing 71.9% of the total population. Messenger followed with 28.95 million users (60.8%), while TikTok reached 21.1 million users (an increase of 21.2% compared to 2024), and YouTube counted 21.1 million users. Instagram, which is particularly relevant to digital marketing and brand communication, registered 12 million users as of early 2025 and 14.15 million by December 2025, making it the platform with the most concentrated young adult audience for brand discovery (NapoleonCat / Statista, 2025; DataReportal, 2025). LinkedIn reached 5.58 million Algerian users in December 2025, reflecting the platform's growing importance among professionals (NapoleonCat / Statista, 2025).

Figure 8 : Users of social media in Algeria



Source : NapoleonCat / Statista (2025) ; DataReportal(2025)

The figure establishes that the Algerian online consumer operates primarily through a mobile-first, social media-driven digital environment, with Facebook, Instagram, TikTok, and WhatsApp constituting the main channels through which brands interact with their audience. The 25–34 age group represents the largest user segment on both Facebook and Instagram.

3. E-Commerce Behavior and Online Purchasing Habits

While Algeria's social media and internet adoption figures are robust, its e-commerce market remains in a relatively early stage of development, characterized by significant growth potential alongside persistent structural challenges. According to Statista Market Forecasts (2024), Algeria's e-commerce market is projected to grow at an annual rate of 9.62% between 2024 and 2029, reaching a market volume of USD 2.051 billion by 2029. The number of e-commerce users is forecast to increase from approximately 7.05 million in 2024 to 9.35 million by 2029, reflecting a growing but still relatively modest user penetration rate of 16.3% in 2024 (Statista, 2024). The UNCTAD eTrade Readiness Assessment of Algeria (2025) provides further detail on the structural characteristics of the Algerian e-commerce landscape. The number of registered e-commerce businesses in Algeria has grown at an average annual rate of 92% since 2020, and online payment transactions for goods and services tripled between 2020 and 2024, reflecting accelerating commercial digitalization. However, cash on delivery remains the dominant payment mode, accounting for approximately 90% of online transactions, which reflects persistent consumer distrust toward electronic payment systems and highlights brand trust as a particularly critical variable in the Algerian online purchasing context (UNCTAD, 2025). Consumer trust in online payments and data security remains a decisive barrier to more widespread e-commerce adoption in Algeria. Euromonitor International (2025) notes that despite significant e-commerce progress, consumer confidence in online payments is still relatively low, and that it is expected to improve gradually as consumers accumulate digital experience and as the necessary regulatory and infrastructural frameworks are put in place. This trust sensitivity directly conditions the population's reception of AI-driven personalization Algerian consumers who are already cautious about digital transactions are particularly attentive to how brands use their behavioral data, making the ethical and transparent use of AI personalization systems a critical precondition for positive consumer engagement and loyalty outcomes.

4. Profile of the Algerian Online Consumer and Research Relevance

The statistical overview presented in Sections 1 through 3 reveals a coherent and empirically grounded profile of the Algerian online consumer. This profile is characterized by five defining features that are directly relevant to the objectives of the present study.

First, the Algerian online consumer is predominantly young and mobile-centric. The largest user groups on Instagram and Facebook are aged 25 to 34, and internet access occurs almost exclusively through smartphones. This mobile-first orientation means that AI-driven personalization, delivered through social media advertising, WhatsApp messaging, and mobile-optimized website experiences, reaches the Algerian consumer in the primary digital environment they inhabit.

Second, social media platforms, particularly Facebook, Instagram, and increasingly TikTok, function as the principal channels for brand discovery, information search, and consumer-brand interaction in Algeria. The statistical data confirms that over 70% of Algerian internet users are active on at least one social media platform, making social media the most important battleground for AI-driven personalization strategies targeting this population.

Third, brand trust is a particularly critical and sensitive variable among Algerian online consumers, given the dominance of cash on delivery (90% of e-commerce transactions) and the persistent consumer reluctance to share financial and personal data online. This trust sensitivity means that AI-driven personalization, when perceived as transparent and beneficial, has a strong potential to generate differentiation and loyalty, while intrusive or opaque personalization practices risk generating significant consumer resistance.

Fourth, the Algerian e-commerce market is growing rapidly but remains structurally underdeveloped relative to the size of the internet user population. The gap between internet penetration (76.9%) and e-commerce user penetration (16.3%) suggests that most Algerian online consumers are actively engaged with digital content and social media but have not yet fully converted their digital engagement into transactional e-commerce behavior. This gap positions AI-driven personalization as a potentially powerful tool for bridging the engagement-conversion divide, by delivering the relevance and trust-building interactions that move consumers from passive content engagement to active brand loyalty and purchasing commitment.

Fifth, the rapid growth of the Algerian digital consumer market, with internet users increasing by 2.7 million in a single year and social media users by 700,000 individuals, indicates that the environment studied in this research is dynamic and rapidly evolving. The findings of this study will therefore not only be academically significant but also timely and practically relevant for brands and marketers seeking to understand and respond to the emerging Algerian online consumer landscape.

Taken together, these characteristics confirm that Algeria constitutes a distinct, empirically grounded, and practically important research context for investigating the impact of AI-driven personalization on customer engagement and brand loyalty among online consumers, which justifies the selection of this national context as the empirical setting of the present study.

Section 2: Methodological Framework

This section describes the methodological approach of this study in relation to the choice of research design, data collection methods and data analysis processes, in order to address the impact of AI-driven personalization on customer engagement and brand loyalty among Algerian online consumers. A quantitative approach through a cross-sectional online survey has been selected as the most appropriate means of data collection. This section provides a detailed account of the research philosophy, the measurement of key variables, sampling strategy, and statistical methods selected.

1. Research Positioning and Design

1.1 Epistemological Stance

Epistemology is a branch of philosophy concerned with the nature, scope, and limits of human knowledge. It investigates the criteria and methods through which knowledge claims can be evaluated and aims to understand how we acquire reliable information about the world (Audi, 2011). The epistemological stance of a study determines the nature of the relationship between the researcher and the object of study, and directly shapes the methodological decisions that follow.

This study adopts a positivist epistemological stance. Positivism holds that reality can be observed and measured with objectivity, and that knowledge is valid only if it is empirically based and logically analyzed through structured quantitative methods. Positivist researchers seek to find patterns, regularities, and cause-and-effect relationships that can be generalized. In this regard, strict adherence to objectivity and replicability is essential (Saunders, Lewis, & Thornhill, 2023). The positivist paradigm is appropriate for this study because its objective is to test hypothesized causal relationships between AI-driven personalization, customer engagement, and brand loyalty through numerical data collected from Algerian online consumers, thereby allowing statistical analysis and objective measurement.

1.2 Research Approach

According to (Saunders et al., 2023), there are two main research approaches: deductive and inductive. The deductive approach starts from existing theories and tests them through empirical observation, while the inductive approach starts from observations and builds new theories from patterns in the data. This study specifically follows the deductive approach, as it begins with an established body of theoretical and empirical literature reviewed in Chapter 1, leading to the formulation of a set of formal hypotheses, and then tests those hypotheses against data collected from Algerian online consumers. The figure below illustrates the steps of this deductive process. Given the non-normal distribution of the data, appropriate non-parametric statistical methods were used for hypothesis testing.

Table 4 :The Research Process Used

Research Process Step	**Choice**
Research philosophy	Positivism
Research approach	Deductive
Research strategy	Survey (online questionnaire)
Methodological choice	Quantitative (mono-method)
Time horizon	Cross-sectional
Data collection and analysis	Questionnaire + IBM SPSS + PROCESS macro (Hayes)

Source: Authors, inspired by Saunders et al. (2023)

The deductive process followed in this study can be summarized as follows: the literature reviewed in Chapter 1 on AI-driven personalization, customer engagement, and brand loyalty generates the following hypotheses, which are then submitted to empirical testing:

H1: AI-driven personalization in digital marketing has a positive and significant effect on brand loyalty among Algerian online consumers.

• H2: AI-driven personalization in digital marketing has a positive and significant effect on customer engagement among Algerian online consumers.

• H3: Customer engagement has a positive and significant effect on brand loyalty among Algerian online consumers.

• H4: Customer engagement mediates the relationship between AI-driven personalization in digital marketing and brand loyalty among Algerian online consumers.

• H5 : The relationship between AI-driven personalization and brand loyalty differs according to Algerian online consumers' demographic characteristics.

- H5a:The relationship between AI-driven personalization and brand loyalty differs according to consumers' age.

- H5b: The relationship between AI-driven personalization and brand loyalty differs according to consumers' gender.

- H5c: The relationship between AI-driven personalization and brand loyalty differs according to consumers' online shopping frequency.

- H5d: The relationship between AI-driven personalization and brand loyalty differs according to consumers' educational level.

1.3 Research Strategy

The survey strategy is typically linked to the deductive research approach and is widely used in business and management studies. It is particularly effective for addressing questions about the nature and strength of relationships between variables in a large population, making it well-suited for this study. Surveys allow researchers to gather structured data from a substantial number of respondents efficiently and cost-effectively (Saunders et al., 2023). An online questionnaire was distributed to Algerian consumers through social media platforms, enabling rapid and structured data collection from the target population.

1.4 Methodological Choice

This study follows a quantitative mono-method approach. Quantitative research focuses on measuring and analyzing numerical data to understand the existence, strength, and direction of relationships between variables. It uses structured methods to collect data that can be statistically tested and generalized. Quantitative techniques are effective at analyzing large populations and enabling researchers to generalize findings from the studied sample to a broader group (Hair, Black, Babin, & Anderson, 2010). Accordingly, this study uses a structured questionnaire with Likert-scale items to collect numerical data that are then subjected to regression analysis, mediation analysis, and group comparison tests.

1.5 Time Horizon

This study is designed as a cross-sectional study, consistent with the time-sensitive nature of academic research. The data collection aimed to capture a snapshot of Algerian online consumers' perceptions of AI-driven personalization and their levels of engagement and brand loyalty at a single point in time (Saunders et al., 2023). This design is appropriate given that the constructs measured are sufficiently stable in the short term to produce meaningful and reliable measurements within a single data collection window.

2. Data Collection Method and Instrument

2.1 Data Collection Method

In this study, data were collected using a structured questionnaire as the primary data collection instrument. The collected data were then analyzed using IBM SPSS Statistics and the PROCESS macro to run statistical tests and generate the results presented in Chapter 3. Primary data collection was preferred because it allows the information gathered to directly address the research objectives, represents the current perspectives of the target population, and matches the specific characteristics of the study context namely Algerian online consumers interacting with AI-driven brand communications through social media and digital platforms.

2.2 Questionnaire Structure

To examine the impact of AI-driven personalization on customer engagement and brand loyalty among Algerian online consumers, a questionnaire was developed and distributed online using Google Forms. The questionnaire utilized a 5-point Likert scale and consisted of six sections, each designed to measure specific constructs related to the study variables. The three main variables are structured as follows:

The independent variable, AI-driven personalization, is measured through three dimensions: perceived relevance, which evaluates whether personalized content matches consumers' interests and profiles; recommendation accuracy, which assesses the precision of AI-generated product and service suggestions; and perceived usefulness, which measures the degree to which personalization improves the consumer's online experience.

The mediating variable, customer engagement, is measured through three dimensions: cognitive engagement, which captures the consumer's attentional and reflective processing of personalized brand content; emotional engagement, which measures the positive affect and sense of belonging generated by personalized interactions; and behavioral engagement, which records observable actions such as liking, sharing, commenting, and brand recommendation.

The dependent variable, brand loyalty, is measured through two dimensions: attitudinal loyalty, which captures the consumer's preference, attachment, and commitment to the brand; and behavioral loyalty, which records repeat purchase intentions and active recommendation behaviors. The study variables are summarized in the table below.

Table 5: Variables of the Study

Variable	**Type**	**Dimensions**	**Number of Items**
AI-Driven Personalization	Independent Variable (IV)	Perceived Relevance Recommendation Accuracy Perceived Usefulness	9 items (Q7–Q15)
Customer Engagement	Mediating Variable (MV)	Cognitive Engagement Emotional Engagement Behavioral Engagement	9 items (Q16–Q24)
Brand Loyalty	Dependent Variable (DV)	Attitudinal Loyalty Behavioral Loyalty	6 items (Q25–Q30)

Source: Authors

2.3 Questionnaire Administration

The questionnaire was first developed based on an extensive review of the previous studies examined in Chapter 1. The initial version was then refined with the recommendations of three academic experts in marketing and research methodology, who assessed the clarity, relevance, and comprehensiveness of the items. Following this face validity review, a pilot test was conducted with eight respondents representative of the target population to verify that all questions were clearly understood and that the overall instrument was well-calibrated in terms of length and cognitive demand. The final version of the questionnaire was then administered online using Google Forms, distributed to Algerian online consumers through Instagram, Facebook, WhatsApp, and Messenger. Respondents were informed of the academic purpose of the study and assured of their full anonymity and confidentiality. A total of 400 valid responses were collected and used in the subsequent analysis.

2.4 Measurement Scale

In this study, a Likert scale was used to measure all substantive variables in the questionnaire. The Likert scale was chosen because it allows respondents to express varying degrees of agreement or disagreement, providing more nuanced and reliable insights than simple binary questions. Moreover, this scale is well-known for its simplicity, flexibility, and ability to convert subjective opinions into quantitative data, which facilitates efficient statistical analysis (Hair et al., 2010). The scale used in this study ranges from 1 to 5, as detailed in the table below.

Table 6: Likert Scale Response Options (1 to 5)

Scale Point	**Description**	**Label**
1	Extreme disagreement	Strongly disagree
2	Disagreement	Disagree
3	Neutral	Neither agree nor disagree
4	Agreement	Agree
5	Extreme agreement	Strongly agree

Source: Authors, based on Hair et al. (2010)

2.5 Data Analysis

BM SPSS Statistics (version 26) is used in this study for data analysis, supplemented by the PROCESS macro (Model 4) developed by Andrew F. Hayes (2018) for mediation analysis. SPSS was selected due to its reliability and extensive application in social science and business research. It enabled the summarization of questionnaire responses, checking of measurement reliability through Cronbach's alpha, testing of normality, and assessment of the relationships between AI-driven personalization, customer engagement, and brand loyalty through correlation and regression analyses. The PROCESS macro, run within SPSS, was specifically used to test the mediation hypothesis (H4) using bootstrapping with 5,000 resamples, generating a 95% bias-corrected confidence interval for the indirect effect.

Group difference tests were conducted using non-parametric methods: the Mann–Whitney U test for gender (H5b) and the Kruskal–Wallis test for age, shopping frequency, and education level (H5a, H5c, H5d), due to the non-normal distribution of the data.

The wide variety of statistical output and visualization options made the results easier to interpret and present with precision.

3. Population and Sampling Design

3.1 Study Population

The study population consists of Algerian nationals who are regular internet users and who have previously interacted with personalized brand content online, encompassing individuals active on social media platforms, e-commerce websites, or digital communication channels. According to DataReportal (2025), Algeria had 36.2 million internet users at the beginning of 2025, representing 76.9% of the total population, with 25.6 million active social media users.

Given the large size and dispersed nature of this population, the sample size was determined using Cochran's formula for large populations, which is appropriate when the population exceeds 1 million:

$$n_0 = \frac{Z^2 \times p(1-p)}{e^2}$$

Where:

- $Z=1.96$ (confidence level of 95%)
- $p=0.5$ (maximum variability assumption)
- $e=0.05$ (margin of error)

$$n_0 = \frac{(1.96)^2 \times 0.5(1-0.5)}{(0.05)^2} = \frac{3.8416 \times 0.25}{0.0025} = \frac{0.9604}{0.0025} = 384.16$$

Thus, the required sample size is approximately 384 respondents.

Accordingly, a survey questionnaire was distributed to a representative sample to generate findings that accurately reflect the experiences and perceptions of Algerian online consumers regarding AI-driven personalization and its effects on their engagement and brand loyalty.

3.2 Sample Size

The final sample of this study consists of 400 valid and complete responses. This sample size meets and slightly exceeds the minimum threshold recommended by Cochran’s formula for large populations (Cochran, 1977), as established in the previous section.

In addition, the sample size is considered appropriate and sufficient for the statistical analyses applied. For regression analysis, a minimum of 10 observations per predictor variable is recommended (Hair et al., 2010). Given that the maximum number of predictors included in any regression model in this study is three, the sample of 400 responses substantially exceeds this requirement.

Furthermore, for mediation analysis using bootstrapping through the PROCESS macro, a minimum of 200 observations is recommended to ensure reliable confidence interval estimation, with samples between 200 and 400 considered robust (Hayes, 2018).

Therefore, the collected sample of 400 responses provides strong statistical power and supports the reliability and validity of the findings related to AI-driven personalization, customer engagement, and brand loyalty among Algerian online consumers.

3.3 Sampling Method

In this study, a non-probability convenience sampling method was used to distribute the questionnaire to the maximum number of eligible respondents possible through social media platforms and digital messaging applications. This method was chosen because the target population of Algerian online consumers is large, geographically dispersed, and primarily accessible through digital channels, making probability sampling methods practically unfeasible within the time and resource constraints of this master's thesis research (Saunders et al., 2023). To partially reduce selection bias, the questionnaire was distributed across multiple platforms Instagram, Facebook, WhatsApp, and Messenger to reach respondents with diverse demographic profiles in terms of age, gender, educational level, and online shopping frequency.

4. Measurement Quality: Validity and Reliability

4.1 Validity of the Instrument

The validity of the questionnaire was assessed at two levels. Face validity was established through the review of three academic experts in marketing and research methodology, who evaluated whether each item adequately represented its intended construct and whether the instrument as a whole was conceptually coherent. Their recommendations led to minor wording adjustments before the pilot test. Content validity was ensured by grounding all measurement items in the validated constructs from the literature reviewed in Chapter 1, drawing on established scales from Brodie et al. (2011), Kumar and Pansari (2017), Oliver (1999), and Dwivedi et al. (2023). Internal consistency validity was further assessed through item-total correlations within each subscale, the results of which are reported in Chapter 3.

4.2 Reliability of the Instrument

The reliability of each multi-item scale was assessed using Cronbach's alpha coefficient, which measures the internal consistency of items intended to reflect the same underlying construct. A Cronbach's alpha of 0.70 or above is considered acceptable for academic research, values above 0.80 indicate good reliability, and values above 0.90 indicate excellent reliability (Hair et al., 2010). Cronbach's alpha was computed for each of the eight subscales and for each of the three composite variables. The full reliability results are reported in Chapter 3, Section 1.3.

4.3 Parametric test Assumptions

Before applying statistical analyses, the assumption of normality was tested using the Kolmogorov-Smirnov test for each of the three main variables.

A significant result ($p < 0.05$) indicates that the normality assumption is not met, and the results are reported in Chapter 3, Section 1.4. Therefore, the data are not normally distributed, and non-parametric statistical tests were employed for hypothesis testing. In addition, regression analysis was conducted using the PROCESS macro to examine the mediating effect.

5. Data Processing and Analysis Methods

5.1 Data Processing Tools

IBM SPSS Statistics (version 26) was used for all data processing and statistical analyses, supplemented by the PROCESS macro (Hayes, 2018) for mediation analysis. Responses collected through Google Forms were first exported to Microsoft Excel for data cleaning, verification of completeness, exclusion of ineligible responses that failed the screening questions, and coding of categorical demographic variables before being imported into SPSS for statistical processing.

5.2 Statistical Analysis Techniques

The statistical analysis was structured sequentially to address all research hypotheses. Descriptive statistics, including means, standard deviations, and frequency distributions, were first computed to characterize the sample and the main variables. Reliability analysis using Cronbach's alpha was conducted for all scales. Normality testing using the Kolmogorov-Smirnov test was applied to each composite variable. Spearman correlation analysis was used to examine bivariate relationships between the three main variables, providing preliminary evidence for H1, H2, and H3. Multiple linear regression was then applied to formally test H1 (IV - DV), H2 (IV - MV), and H3 (MV - DV). Mediation analysis for H4 was conducted using the PROCESS macro Model 4 (Hayes, 2018) with bootstrapping of 5,000 resamples; if the 95% bias-corrected confidence interval for the indirect effect does not include zero, mediation is confirmed as either partial (direct effect remains significant) or full (direct effect becomes non-significant). Finally, a Mann-Whitney U test was used to test H5b (gender), and a Kruskal-Wallis test was used to test H5a (age), H5c (online shopping frequency), and H5d (educational level).

Table 7: Summary of Statistical Analysis Plan

Hypothesis	**Statistical Test**	**Software**
Descriptive overview	Descriptive statistics (means, SD, frequencies)	SPSS
Reliability	Cronbach's Alpha ($\alpha \geq 0.70$)	SPSS
Normality	Kolmogorov-Smirnov test ($p > 0.05$)	SPSS
H1, H2, H3 preliminary	Spearman Correlation	SPSS
H1 - IV: DV	Multiple Linear Regression	SPSS
H2 - IV: MV	Multiple Linear Regression	SPSS
H3 - MV: DV	Multiple Linear Regression	SPSS
H4 - Mediation	PROCESS Macro Model 4 (Hayes, 2018)Bootstrapping: 5,000 resamples 95% CI must exclude 0	SPSS + PROCESS
H5b - Gender	Mann–Whitney U test	SPSS
H5a / H5c / H5d	Kruskal–Wallis test	SPSS

Source: Authors, based on Hair et al. (2010); Hayes (2018)

Conclusion

This chapter outlined both the contextual and methodological foundations of the empirical investigation. The contextual analysis highlighted the rapid growth of internet usage, social media engagement, and digital consumption in Algeria, confirming the relevance of studying AI-driven personalization and brand loyalty within the Algerian online market. The discussion also emphasized the specific characteristics of Algerian online consumers, particularly the importance of trust, social media interaction, and personalized digital experiences in shaping consumer behavior.

From a methodological perspective, the chapter justified the adoption of a positivist and quantitative research design based on a structured online survey administered to Algerian online consumers. The chapter detailed the procedures related to data collection, sampling, questionnaire design, and statistical analysis techniques used to ensure the validity and reliability of the research findings. Appropriate statistical methods, including reliability testing, regression analysis, mediation analysis, and non-parametric tests, were selected to examine the proposed relationships between the study variables and test the research hypotheses.

Overall, this chapter established the methodological rigor of the study and prepared the ground for the presentation and discussion of the empirical results in the following chapter.

CHAPTER III : RESULTS AND DISCUSSION

This chapter presents the empirical results and their discussion based on data collected from 400 Algerian online consumers through an online questionnaire. It first examines the quality of the data through preliminary tests, then analyzes the sample profile, descriptive statistics, and the hypotheses related to AI-driven personalization, customer engagement, and brand loyalty, including mediation and moderation effects. The second part discusses these findings by comparing them with previous studies and interpreting them within the Algerian e-commerce context, before highlighting the main theoretical and managerial implications.

Section 01: Results

This first section reports the empirical results obtained from the questionnaire administered to 400 Algerian online consumers. The presentation follows a logical sequence: it begins with the preliminary tests aimed at verifying the quality and suitability of the dataset for further analysis, continues with a description of the sociodemographic and behavioral profile of the sample, then presents the descriptive statistics of the three composite study variables, and finally reports the inferential tests used to evaluate each of the research hypotheses.

1. Data Screening and Preliminary Analysis

Prior to testing the research hypotheses, three preliminary tests were performed to assess the quality of the data and the suitability of the measurement instrument. These tests concern the inspection of missing values, the verification of the normality of the distributions of the main variables, and the assessment of the internal consistency of the measurement scale.

1.1. Missing Values

The questionnaire was distributed online via Google Forms with all items configured as mandatory, which prevented respondents from submitting incomplete questionnaires. As a result, the dataset of 400 valid responses contains no missing values. The results of the missing-values inspection produced by SPSS are summarized in Table 8 below.

Table 8: Distribution of Missing Values Across the Study Variables

Variable / Construct	Valid Responses (N)	Missing Values	Percentage of Missing (%)
Age	400	0	0.0
Gender	400	0	0.0
Online Shopping Frequency	400	0	0.0
Educational Level	400	0	0.0
AI-Driven Personalization (VI) – 9 items	400	0	0.0
Customer Engagement (VMED) – 9 items	400	0	0.0
Brand Loyalty (VD) – 6 items	400	0	0.0

Source: Self-developed based on IBM SPSS 27 outputs.

As shown in Table 8, all demographic variables and all 24 measurement items related to the three constructs of the study, along with the 4 sociodemographic and behavioral items, present 400 valid observations and 0 missing values, confirming the integrity and completeness of the dataset for the subsequent analyses.

1.2. Reliability Test

The internal consistency of the measurement scale was assessed using Cronbach's Alpha coefficient. According to Nunnally (1978), an Alpha value equal to or higher than 0.70 is considered acceptable for research in the social sciences, while values between 0.80 and 0.90 indicate good reliability and values above 0.90 indicate excellent reliability (George & Mallery, 2003). The Alpha coefficient was first computed for each construct separately and then for the overall scale. The questionnaire comprises a total of 28 items: 24 items measuring the three main constructs (9 for AI-driven personalization, 9 for customer engagement, and 6 for brand loyalty) and 4 items capturing the sociodemographic and behavioral profile of the respondents (age, gender, educational level, and online shopping frequency). The reliability results are reported in Tables 9 and 10.

Table 9: Reliability of Each Study Variable

Variable	Number of Items	Cronbach's Alpha (α)	Interpretation
AI-Driven Personalization (Independent Variable – VI)	9	0.743	Acceptable
Customer Engagement (Mediating Variable – VMED)	9	0.698	Acceptable (≈ 0.70)
Brand Loyalty (Dependent Variable – VD)	6	0.730	Acceptable

Source: Self-developed based on IBM SPSS 27 outputs.

As presented in Table 9, each of the three constructs reaches or approximates the recommended threshold of 0.70. The independent variable (AI-driven personalization) shows good consistency ($\alpha = 0.743$), the dependent variable (brand loyalty) reaches $\alpha = 0.730$, and the mediating variable (customer engagement) reaches $\alpha = 0.698$, which is considered acceptable in exploratory research and rounds to the 0.70 benchmark. These individual reliability values confirm that each construct measures consistently the dimension it is intended to capture.

Table 10: Overall Reliability of the Measurement Scale

Measurement Scale	Number of Items	Cronbach's Alpha (α)
Full Scale	26	0.864

Source: Self-developed based on IBM SPSS 27 outputs.

As displayed in Table 10, the overall Cronbach's Alpha value of 0.864 obtained on all 28 items (24 construct items and 4 sociodemographic/behavioral items) largely exceeds the recommended threshold and reaches the level considered as good to excellent (George & Mallery, 2003). This confirms the high internal consistency of the items used and supports the suitability of the questionnaire for further statistical analysis.

1.3. Normality Test

To examine whether the three composite variables of the study, AI-driven personalization (VI), customer engagement (VMED), and brand loyalty (VD) follow a normal distribution, the Kolmogorov–Smirnov (K-S) test with Lilliefors significance correction was applied. The K-S test is well suited to large samples ($N \geq 50$) and is widely used as a goodness-of-fit test for normality. The results are reported in Table 11.

Table 11: Results of the Kolmogorov–Smirnov Normality Test

Variable	K-S Statistic	df	Sig. (p-value)	Decision
VI (AI-Driven Personalization)	0.130	400	< 0.001	Non-normal
VMED (Customer Engagement)	0.131	400	< 0.001	Non-normal
VD (Brand Loyalty)	0.152	400	< 0.001	Non-normal

Source: Self-developed based on IBM SPSS 27 outputs.

As shown in Table 11, the asymptotic significance values (Sig. < 0.001) are below the conventional threshold of 0.05 for all three variables. This indicates that the distributions of the three composite variables significantly deviate from normality. Consequently, the distributions are considered non-normal. Based on this conclusion, non-parametric tests (Spearman correlation, Mann-Whitney U test, and Kruskal-Wallis H test) were employed for the bivariate analyses, while a bootstrap-based mediation analysis (PROCESS Macro Model 4) was used to ensure robustness against the violation of the normality assumption.

2. Sociodemographic and Behavioral Profile of the Sample

The sample consists of 400 Algerian online consumers who completed the online questionnaire. This sub-section describes the sociodemographic and behavioral profile of the respondents in terms of age, gender, educational level, and online shopping frequency. The first three variables constitute the sociodemographic characteristics, while online shopping frequency reflects a behavioral dimension. The corresponding frequencies and percentages, computed from the SPSS frequency tables, are summarized below.

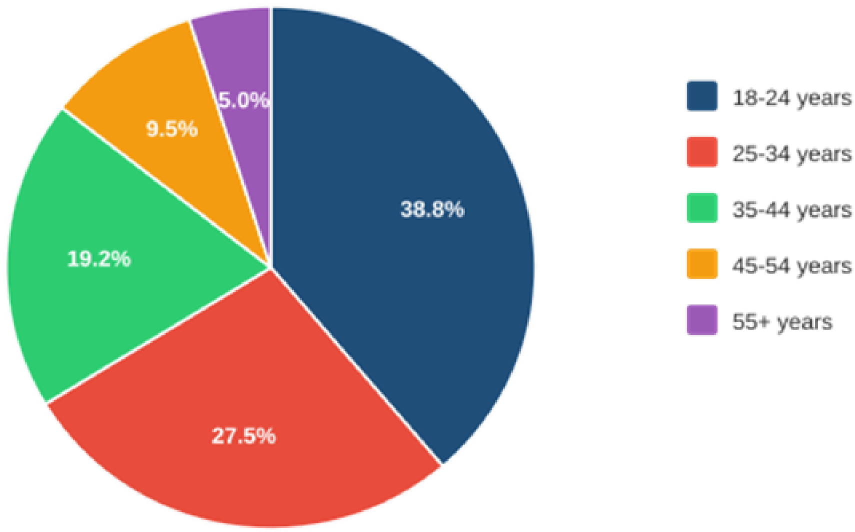
2.1. Age Distribution

Table 12: Age Distribution of Respondents

Age Group	Frequency	Percentage (%)
18 – 24 years	155	38.75
25 – 34 years	110	27.50
35 – 44 years	77	19.25
45 – 54 years	38	9.50
55 years and over	20	5.00
Total	400	100.00

Source: Self-developed based on IBM SPSS 27 outputs.

Figure 9: Age Distribution of Respondents



Source: Self-developed based on IBM SPSS 27 outputs.

As shown in Table 12, the age distribution of the sample reveals a predominantly young profile. The largest age group is composed of respondents aged between 18 and 24 years (155 respondents, 38.75%), followed by those aged 25–34 (110 respondents, 27.50%) and 35–44 (77 respondents, 19.25%). The 45–54 age group includes 38 respondents (9.50%), while only 20 respondents (5.00%) are aged 55 and over. Together, respondents aged between 18 and 34 years represent 66.25% of the sample, reflecting the youth-driven nature of the Algerian online consumer base.

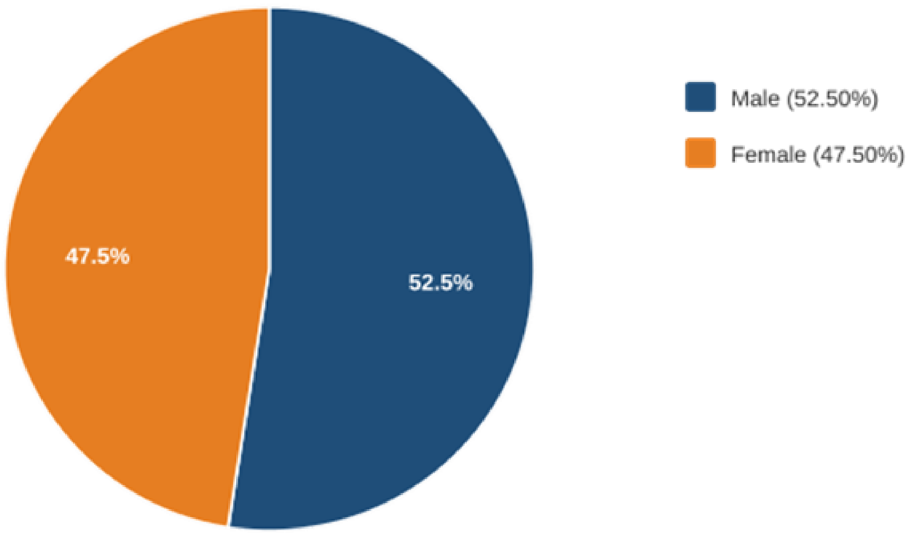
2.2. Gender Distribution

Table 13: Gender Distribution of Respondents

Gender	Frequency	Percentage (%)
Male (H)	210	52.50
Female (F)	190	47.50
Total	400	100.00

Source: Self-developed based on IBM SPSS 27 outputs.

Figure 10: Gender Distribution of Respondents



Source: Self-developed based on IBM SPSS 27 outputs.

As reported in Table 13, the sample comprises 210 male respondents (52.50%) and 190 female respondents (47.50%), reflecting a balanced gender representation. This near-parity between male and female participants is favorable for analyzing potential gender-based differences in the relationship between AI-driven personalization and brand loyalty (H5b).

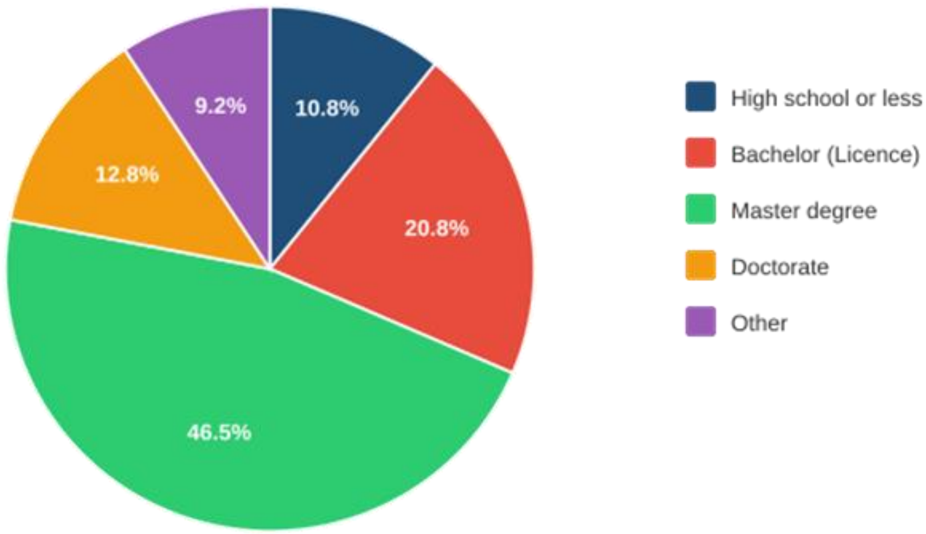
2.3. Educational Level

Table 14: Distribution of Respondents by Educational Level

Educational Level	Frequency	Percentage (%)
High school or less	43	10.75
Bachelor’s degree (Licence)	83	20.75
Master’s degree	186	46.50
PHD	51	12.75
Other	37	9.25
Total	400	100.00

Source: Self-developed based on IBM SPSS 27 outputs.

Figure 11: Educational Level of Respondents



Source: Self-developed based on IBM SPSS 27 outputs.

Table 14 illustrates the educational profile of the sample. Master's degree holders constitute the largest segment (46.50%), followed by Bachelor's degree holders (20.75%), PHD holders (12.75%), High school or less (10.75%), and Other (9.25%). Overall, more than 80% of respondents hold at least a Bachelor's degree, indicating that the sample is composed of relatively highly educated respondents, who are likely to be familiar with digital technologies and AI-personalized online shopping platforms.

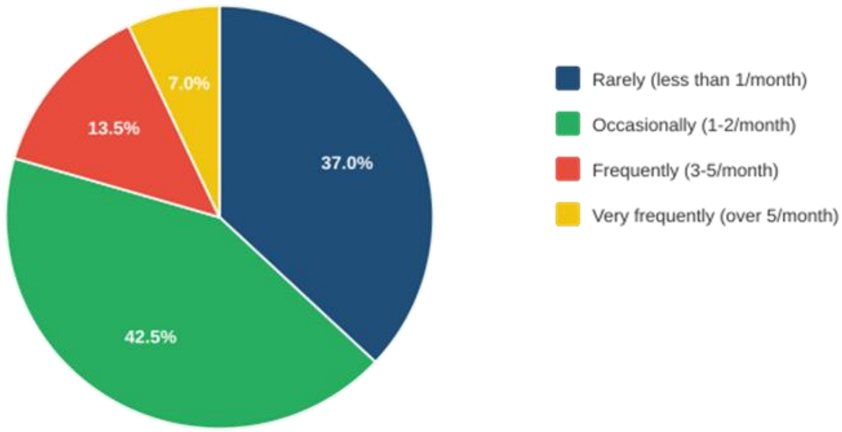
2.4. Online Shopping Frequency (Behavioral Profile)

Table 15: Distribution of Respondents by Online Shopping Frequency

Online Shopping Frequency	Frequency	Percentage (%)
Rarely (less than once per month)	148	37.00
Occasionally (1 to 2 times per month)	170	42.50
Frequently (3 to 5 times per month)	54	13.50
Very frequently (more than 5 times per month)	28	7.00
Total	400	100.00

Source: Self-developed based on IBM SPSS 27 outputs.

Figure 12: Online shopping Frequency of Respondents



Source: Self-developed based on IBM SPSS 27 outputs.

Table 15 shows the distribution of respondents according to their online shopping frequency. Occasional shoppers (1 to 2 times per month) form the largest category with 42.50% of the sample, followed by rare shoppers (37.00%), frequent shoppers (13.50%), and very frequent shoppers (7.00%). This pattern is consistent with the still-developing nature of e-commerce in Algeria, characterized by gradual but expanding online shopping habits.

3. Descriptive Analysis of the Study Variables

The descriptive statistics of the three main variables AI-driven personalization (VI), customer engagement (VMED), and brand loyalty (VD) were computed based on the average scores of their respective items, all measured on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). To interpret the resulting means, the Likert scale was divided into five equal intervals of width 0.80, each associated with a level of agreement. The interpretation grid is presented in Table 16.

Table 16: Interpretation Grid of Mean Scores on the 5-Point Likert Scale

Mean Interval	Response Trend	Level of Agreement
[1.00 – 1.80[	Strongly Disagree	Very Low
[1.80 – 2.60[	Disagree	Low
[2.60 – 3.40[	Neither Agree nor Disagree	Moderate
[3.40 – 4.20[	Agree	High
[4.20 – 5.00]	Strongly Agree	Very High

Source: Self-developed based on the Likert scale used.

3.1. Descriptive Statistics of the Independent Variable (AI-Driven Personalization)

Table 17: Descriptive Statistics of AI-Driven Personalization (VI)

Dimension	Min	Max	Mean	SD	Trend
VID1: Personalized Content	1.33	5.00	3.71	0.747	Agree
VID2: Personalized Recommendations	1.00	5.00	3.74	0.727	Agree
VID3: Adapted Offers and Communications	1.33	5.00	3.90	0.743	Agree
VI (Composite Variable)	1.67	5.00	3.78	0.601	Agree

Source: Self-developed based on IBM SPSS 27 outputs.

As shown in Table 17, the three dimensions of AI-driven personalization yield mean scores between 3.71 and 3.90, all of which fall within the interval [3.40 – 4.20[, corresponding to the "Agree" response trend. The composite mean of 3.78 (SD = 0.601) confirms that, on average, Algerian online consumers agree that the brands they interact with deploy AI-driven personalization actions. The dimension VID3 (adapted offers and communications) records the highest mean (3.90), suggesting that respondents are particularly aware of personalized offers and communications targeted at them.

3.2. Descriptive Statistics of the Mediating Variable (Customer Engagement)

Table 18: Descriptive Statistics of Customer Engagement (VMED)

Dimension	Min	Max	Mean	SD	Trend
VMD1: Cognitive Engagement	1.33	5.00	3.83	0.730	Agree
VMD2: Affective Engagement	1.33	5.00	3.89	0.763	Agree
VMD3: Behavioral Engagement	1.00	5.00	3.67	0.787	Agree
VMED (Composite Variable)	1.56	4.89	3.80	0.600	Agree

Source: Self-developed based on IBM SPSS 27 outputs.

As shown in Table 18, the means of the three dimensions of customer engagement vary between 3.67 and 3.89, all situated within the interval [3.40 – 4.20[, corresponding to the "Agree" response trend. The composite mean of 3.80 (SD = 0.600) indicates that respondents tend to engage actively with the brands that personalize their experience. Affective engagement (VMD2) records the highest mean (3.89), suggesting that emotional involvement is a particularly strong component of consumers' engagement with personalized brands.

3.3. Descriptive Statistics of the Dependent Variable (Brand Loyalty)

Table 19: Descriptive Statistics of Brand Loyalty (VD)

Dimension	Min	Max	Mean	SD	Trend
VDD1: Attitudinal Loyalty	1.33	5.00	3.79	0.747	Agree
VDD2: Behavioral Loyalty	1.33	5.00	3.90	0.727	Agree
VD (Composite Variable)	1.67	5.00	3.85	0.654	Agree

Source: Self-developed based on IBM SPSS 27 outputs.

As displayed in Table 19, the two dimensions of brand loyalty record mean scores of 3.79 and 3.90, both falling within the "Agree" interval [3.40 – 4.20[. The composite mean of brand loyalty reaches 3.85 (SD = 0.654), revealing a moderately strong loyalty orientation toward brands deploying AI-driven personalization in the Algerian online market.

3.4. Overall Descriptive Statistics of the Three Composite Variables

Table 20: Descriptive Statistics of Brand Loyalty (VD)

Variable	N	Min	Max	Mean	SD	Trend
AI-Driven Personalization (VI)	400	1.67	5.00	3.78	0.601	Agree
Customer Engagement (VMED)	400	1.56	4.89	3.80	0.600	Agree
Brand Loyalty (VD)	400	1.67	5.00	3.85	0.654	Agree

Source: Self-developed based on IBM SPSS 27 outputs.

As shown in Table 20, the mean scores of all three composite variables are well above the midpoint of the Likert scale (3.00) and fall within the "Agree" interval [3.40 – 4.20[. Brand loyalty (VD) obtains the highest mean (M = 3.85, SD = 0.654), followed by customer engagement (VMED) (M = 3.80, SD = 0.600) and AI-driven personalization (VI) (M = 3.78, SD = 0.601). Based on the interpretation grid presented in Table 9, the response trend for the three constructs is "Agree", reflecting a globally positive perception. The relatively low standard deviations (all below 0.66) indicate moderate dispersion around the means, suggesting a homogeneous tendency among respondents in their evaluations of these constructs.

4. Hypotheses Testing

This sub-section reports the inferential tests used to evaluate the five research hypotheses of the study. Given the non-normal distribution of the data, a combination of parametric and non-parametric techniques was applied: Spearman's correlation as a preliminary bivariate check, multiple linear regression for hypotheses H1, H2, and H3, the PROCESS Macro Model 4 with bootstrap resampling for the mediation hypothesis (H4), and the Mann-Whitney U test and Kruskal-Wallis H test for the demographic and behavioral group differences (H5a to H5d).

4.1. Preliminary Correlation Analysis (Spearman's Rho)

Before performing the regression analyses, Spearman's rho correlation coefficients were computed in order to examine the bivariate relationships between the three main variables of the model. The choice of Spearman's rho rather than Pearson's r is justified by the violation of the normality assumption documented previously.

Table 21: Spearman's Rho Correlation Matrix

Variables	VI	VMED	VD
VI	1.000	0.548**	0.514**
VMED	0.548**	1.000	0.714**
VD	0.514**	0.714**	1.000

Source: Self-developed based on IBM SPSS 27 outputs.

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

As shown in Table 21, all three correlations are positive and statistically significant at the 0.01 level. The strongest association is observed between customer engagement and brand loyalty ($\rho = 0.714$, $p < 0.001$), followed by the correlation between AI-driven personalization and customer engagement ($\rho = 0.548$, $p < 0.001$) and between AI-driven personalization and brand loyalty ($\rho = 0.514$, $p < 0.001$). These preliminary results provide initial evidence of meaningful relationships between the three constructs and justify the deeper testing of the hypothesized causal paths through regression analysis.

4.2. Testing Hypothesis 1 H1: AI-driven personalization in digital marketing has a positive and significant effect on brand loyalty among Algerian online consumers

To test this hypothesis, a multiple linear regression analysis was performed with the three dimensions of AI-driven personalization (VID1, VID2, VID3) as predictors and brand loyalty (VD) as the dependent variable. The results are summarized in Tables 22 and 23.

Table 22: Model Summary and ANOVA – Multiple Linear Regression (H1)

R	R^2	Adj. R^2	Std. Error	F (3, 396)	Sig. (p-value)	
0.571	0.326	0.321	0.539	63.892	< 0.001	

Source: Self-developed based on IBM SPSS 27 outputs.

Table 23: Regression Coefficients – Predicting Brand Loyalty (H1)

Predictor	B (Unstd.)	Std. Error	β (Std.)	t-value	Sig.
(Constant)	1.492	0.172	—	8.661	< 0.001
VID1	0.179	0.044	0.204	4.059	< 0.001
VID2	0.191	0.046	0.213	4.169	< 0.001
VID3	0.250	0.043	0.284	5.766	< 0.001

Source: Self-developed based on IBM SPSS 27 outputs.

As displayed in Tables 22 and 23, the regression model is statistically significant at the 0.001 significance level ($F(3, 396) = 63.892$, $p < 0.001$), and the three predictors collectively explain 32.6% of the variance in brand loyalty ($R^2 = 0.326$, Adjusted $R^2 = 0.321$). All three dimensions of AI-driven personalization significantly contribute to the prediction of brand loyalty at the $\alpha = 0.001$ level, with VID3 showing the strongest standardized contribution ($\beta = 0.284$), followed by VID2 ($\beta = 0.213$) and VID1 ($\beta = 0.204$). These findings support H1: AI-driven personalization has a positive and significant effect on brand loyalty among Algerian online consumers.

Based on the unstandardized coefficients reported in Table 23, the regression equation predicting brand loyalty (VD) from the three dimensions of AI-driven personalization can be written as follows:

$$\mathbf{VD = 1.492 + 0.179 \times VID1 + 0.191 \times VID2 + 0.250 \times VID3}$$

This equation indicates that, holding the other dimensions constant, each one-unit increase in VID1, VID2, and VID3 is associated with an increase in brand loyalty of 0.179, 0.191, and 0.250 units respectively. The intercept of 1.492 represents the baseline level of brand loyalty when all three predictors are equal to zero.

4.3. Testing Hypothesis 2 H2: AI-driven personalization in digital marketing has a positive and significant effect on customer engagement among Algerian online consumers

The same procedure was applied, with VID1, VID2, and VID3 entered as predictors and customer engagement (VMED) as the dependent variable. The results are reported in Tables 24 and 25.

Table 24: Model Summary and ANOVA – Multiple Linear Regression (H2)

R	R²	Adj. R²	Std. Error	F (3, 396)	Sig. (p-value)	
0.601	0.361	0.356	0.482	74.538	< 0.001	

Source: Self-developed based on IBM SPSS 27 outputs.

Table 25: Regression Coefficients – Predicting Customer Engagement (H2)

Predictor	B (Unstd.)	Std. Error	β (Std.)	t-value	Sig.
(Constant)	1.526	0.154	—	9.897	< 0.001
VID1	0.204	0.039	0.254	5.183	< 0.001
VID2	0.192	0.041	0.233	4.676	< 0.001
VID3	0.204	0.039	0.252	5.260	< 0.001

Source: Self-developed based on IBM SPSS 27 outputs.

As shown in Tables 24 and 25, the model is statistically significant at the 0.001 significance level ($F(3, 396) = 74.538$, $p < 0.001$) and explains 36.1% of the variance in customer engagement ($R^2 = 0.361$, Adjusted $R^2 = 0.356$). All three predictors are significant at $\alpha = 0.001$, with relatively comparable standardized coefficients ranging from $\beta = 0.233$ (VID2) to $\beta = 0.254$ (VID1). These results support H2: AI-driven personalization has a positive and significant effect on customer engagement among Algerian online consumers.

Based on the unstandardized coefficients reported in Table 25, the regression equation predicting customer engagement (VMED) from the three dimensions of AI-driven personalization can be written as follows:

$$\mathbf{VMED = 1.526 + 0.204 \times VID1 + 0.192 \times VID2 + 0.204 \times VID3}$$

This equation shows that the three dimensions of personalization contribute almost equally to predicting customer engagement, with the unstandardized coefficients of VID1 and VID3 being equal (0.204) and that of VID2 being slightly lower (0.192).

4.4. Testing Hypothesis 3 (H3: customer engagement has a positive and significant effect on brand loyalty among Algerian online consumers)

A multiple linear regression was conducted with the three dimensions of customer engagement (VMD1, VMD2, VMD3) as predictors and brand loyalty (VD) as the dependent variable. The results are reported in Tables 26 and 27.

Table 26: Model Summary and ANOVA – Multiple Linear Regression (H3)

R	R^2	Adj. R^2	Std. Error	F (3, 396)	Sig. (p-value)
0.764	0.584	0.581	0.423	185.322	< 0.001

Source: Self-developed based on IBM SPSS 27 outputs.

Table 27: Regression Coefficients – Predicting Brand Loyalty from Customer Engagement (H3)

Predictor	B (Unstd.)	Std. Error	β (Std.)	t-value	Sig.
(Constant)	0.714	0.137	—	5.217	< 0.001
VMD1	0.293	0.033	0.327	8.774	< 0.001
VMD2	0.218	0.032	0.254	6.744	< 0.001
VMD3	0.317	0.032	0.382	9.900	< 0.001

Source: Self-developed based on IBM SPSS 27 outputs.

As shown in Tables 26 and 27, the model is highly significant at the 0.001 significance level ($F(3, 396) = 185.322$, $p < 0.001$) and explains 58.4% of the variance in brand loyalty ($R^2 = 0.584$, Adjusted $R^2 = 0.581$), which represents a substantial explanatory power. All three dimensions of customer engagement are significant predictors of brand loyalty at $\alpha = 0.001$, with VMD3 (behavioral engagement) contributing the most ($\beta = 0.382$), followed by VMD1 ($\beta = 0.327$) and VMD2 ($\beta = 0.254$). These results support H3: customer engagement has a positive and significant effect on brand loyalty among Algerian online consumers.

Based on the unstandardized coefficients reported in Table 27, the regression equation predicting brand loyalty (VD) from the three dimensions of customer engagement can be written as follows:

$$\mathbf{VD = 0.714 + 0.293 \times VMD1 + 0.218 \times VMD2 + 0.317 \times VMD3}$$

This equation indicates that behavioral engagement (VMD3) exerts the strongest marginal effect on brand loyalty, since each additional unit on VMD3 produces a 0.317-unit increase in brand loyalty, holding the other dimensions constant.

4.5. Testing Hypothesis 4 (H4: customer engagement mediates the relationship between AI-driven personalization in digital marketing and brand loyalty among Algerian online consumers; Mediation Analysis)

The mediation hypothesis was tested using Hayes' PROCESS Macro Model 4 (Hayes, 2022) with 5,000 bootstrap resamples and a 95% confidence interval. According to the bootstrap procedure, the indirect effect is considered statistically significant when the confidence interval (BootLLCI – BootULCI) does not include zero. The results are summarized in Tables 28 and 29.

Table 28 : Summary of the Mediation Model (PROCESS Macro Model 4) – Direct Paths

Relationship	B (Coeff.)	t-value	p-value	Sig. Level	Decision
VI → VMED (a path)	0.6005	14.989	< 0.001	α = 0.001	Significant
VMED → VD (b path)	0.7146	16.523	< 0.001	α = 0.001	Significant
VI → VD (direct effect c')	0.1905	4.407	< 0.001	α = 0.001	Significant
VI → VD (total effect c)	0.6196	13.816	< 0.001	α = 0.001	Significant

Source: Self-developed based on PROCESS v4.2 Macro outputs.

Table 29: Indirect Effect of VI on VD Through VMED (Bootstrap Method, 5,000 resamples)

Effect	Boot Effect (B)	Boot LLCI	Boot ULCI	Decision
VI → VMED → VD	0.4291	0.3383	0.5256	Mediation confirmed
Completely standardized indirect effect	0.3943	0.3190	0.4671	Mediation confirmed

Source: Self-developed based on PROCESS v4.2 Macro outputs (95% Bootstrap CI).

The mediation analysis using PROCESS Macro Model 4 indicates that AI-driven personalization (VI) has a statistically significant positive total effect on brand loyalty (VD), with a total effect coefficient of B = 0.6196 (significant at $\alpha = 0.001$). After introducing the mediating variable VMED into the model, the direct effect of VI on VD remains statistically significant but decreases in magnitude (B = 0.1905, $p < 0.001$), which is a typical signature of a mediation mechanism.

Regarding the specific paths of the mediation model, AI-driven personalization (VI) has a significant positive effect on customer engagement (VMED) (B = 0.6005, significant at $\alpha = 0.001$), and customer engagement (VMED) significantly affects brand loyalty (VD) (B = 0.7146, significant at $\alpha = 0.001$). The indirect effect of VI on VD through VMED is statistically significant (B = 0.4291), which is further confirmed by the bootstrap 95% confidence interval [0.3383; 0.5256] that does not contain zero.

Moreover, the completely standardized indirect effect ($\beta = 0.3943$) is more than twice as large as the standardized direct effect ($\beta = 0.1751$), which underscores the central role of customer engagement in transmitting the influence of AI-driven personalization to brand loyalty. These results demonstrate that customer engagement partially mediates the relationship between AI-driven personalization and brand loyalty, since both the direct and the indirect effects remain significant. Hypothesis H4 is therefore supported.

4.6. Testing Hypothesis 5 (H5: The relationship between AI-driven personalization and brand loyalty differs according to Algerian online consumers' demographic characteristics)

H5 examines whether the relationship between AI-driven personalization and brand loyalty differs according to selected sociodemographic and behavioral characteristics of Algerian online consumers, namely age (H5a), gender (H5b), online shopping frequency (H5c), and educational level (H5d). Given the violation of normality, the Mann-Whitney U test was used for the dichotomous variable (gender), while the Kruskal-Wallis H test was used for the variables comprising more than two groups.

4.6.1. H5a: The relationship between AI-driven personalization and brand loyalty differs according to consumers' age.

Table 30: Kruskal–Wallis Test Results by Age

Variable	Age Category	N	Mean Rank	H	df	p-value	Decision
VD	18 – 24 years	155	198.53	5.179	4	0.269	Not significant at α = 0.05
	25 – 34 years	110	207.27				
	35 – 44 years	77	210.01				
	45 – 54 years	38	163.18				
	55 years and over	20	212.83				

Source: Self-developed based on IBM SPSS 27 outputs.

As reported in Table 30, the Kruskal-Wallis H test yielded $H(4) = 5.179$ with an asymptotic significance value of 0.269, which is greater than the conventional threshold of $\alpha = 0.05$. Therefore, no statistically significant difference in brand loyalty was found across the five age groups at the 0.05 significance level. H5a is consequently not supported.

4.6.2. H5b: The relationship between AI-driven personalization and brand loyalty differs according to consumers' gender

Table 31: Mann-Whitney U Test Results by Gender

Variable	Group	N	Mean Rank	U	Z	p-value	Decision
VD	Male	210	218.24	16,225.000	-3.241	0.001	Significant at α = 0.01
	Female	190	180.89				

Source: Self-developed based on IBM SPSS 27 outputs.

As displayed in Table 31, the Mann-Whitney U test reveals a statistically significant difference between male and female respondents regarding their brand loyalty scores ($U = 16{,}225.000$; $Z = -3.241$; $p = 0.001$), significant at the $\alpha = 0.01$ level. Male respondents (Mean Rank = 218.24) report a higher level of brand loyalty than female respondents (Mean Rank = 180.89), suggesting that males in the sample exhibit higher loyalty toward AI-personalized brands. H5b is therefore supported.

4.6.3. H5c: The relationship between AI-driven personalization and brand loyalty differs according to consumers' online shopping frequency

Table 32: Kruskal–Wallis Test Results by Online Shopping Frequency

Variable	Shopping Frequency	N	Mean Rank	H	df	p-value	Decision
VD	Rarely (< 1/month)	148	201.97	10.373	3	0.016	Significant at α = 0.05
	Occasionally (1–2/month)	170	187.11				
	Frequently (3–5/month)	54	207.00				
	Very frequently (> 5/month)	28	261.52				

Source: Self-developed based on IBM SPSS 27 outputs.

As shown in Table 32, the Kruskal-Wallis H test indicates a statistically significant difference in brand loyalty across the four groups of online shopping frequency (H(3) = 10.373; p = 0.016), significant at the α = 0.05 level. Examination of the mean ranks shows that the highest level of brand loyalty is observed among very frequent online shoppers (Mean Rank = 261.52), followed by frequent shoppers (207.00), rare shoppers (201.97), and occasional shoppers (187.11). H5c is therefore supported.

4.6.4. H5d: The relationship between AI-driven personalization and brand loyalty differs according to consumers' educational level

Table 33: Kruskal–Wallis Test Results by Educational Level

Variable	Educational Level	N	Mean Rank	H	df	p-value	Decision
VD	High school or less	43	233.55	7.661	4	0.105	Not significant at α = 0.05
	Bachelor's degree (Licence)	83	192.29				
	Master's degree	186	206.26				
	Doctorate	51	173.21				
	Other	37	189.20				

Source: Self-developed based on IBM SPSS 27 outputs.

As shown in Table 33, the Kruskal-Wallis H test yielded H(4) = 7.661 with an asymptotic significance value of 0.105, which exceeds the α = 0.05 threshold. Consequently, no statistically significant difference was found in brand loyalty across the five educational level groups at the 0.05 significance level. H5d is therefore not supported.

4.7. Summary of Hypotheses Testing Results

Table 34: Summary of Hypothesis Testing Results

Hypothesis	Statistical Test	Key Result	Sig. Level	Decision
H1: AI-driven personalization - Brand loyalty	Multiple Linear Regression	$R^2 = 0.326$; $F = 63.892$; $p < 0.001$	$\alpha = 0.001$	Supported
H2: AI-driven personalization - Customer engagement	Multiple Linear Regression	$R^2 = 0.361$; $F = 74.538$; $p < 0.001$	$\alpha = 0.001$	Supported
H3: Customer engagement - Brand loyalty	Multiple Linear Regression	$R^2 = 0.584$; $F = 185.322$; $p < 0.001$	$\alpha = 0.001$	Supported
H4: Mediating role of customer engagement	PROCESS Macro Model 4 (Bootstrap)	Indirect effect = 0.4291; 95% CI [0.3383; 0.5256]; partial mediation	95% CI	Supported
H5a: Differences by age	Kruskal-Wallis H	$H = 5.179$; $p = 0.269$	$\alpha = 0.05$	Not Supported
H5b: Differences by gender	Mann-Whitney U	$U = 16{,}225$; $Z = -3.241$; $p = 0.001$	$\alpha = 0.01$	Supported
H5c: Differences by online shopping frequency	Kruskal-Wallis H	$H = 10.373$; $p = 0.016$	$\alpha = 0.05$	Supported
H5d: Differences by educational level	Kruskal-Wallis H	$H = 7.661$; $p = 0.105$	$\alpha = 0.05$	Not Supported

Source: Self-developed based on IBM SPSS 27 and PROCESS Macro outputs.

Out of the eight tested hypotheses (including the four sub-hypotheses of H5), six are supported by the empirical data (H1, H2, H3, H4, H5b, and H5c), while two are not supported (H5a and H5d). The interpretation and discussion of these findings, in light of the existing literature and within the Algerian context, are presented in Section 02.

Section 02: Discussion of the Findings

This second section is dedicated to the interpretation and critical discussion of the empirical findings presented in Section 01. The discussion is structured around five main components: the quality of the data, the sociodemographic and behavioral characteristics of the sample, the descriptive results of the key variables, the testing of the research hypotheses, and the theoretical and managerial implications derived from the findings. Each result is restated, interpreted, compared with the relevant literature, and contextualized within the specific Algerian e-commerce environment.

2.1. Discussion of Data Quality

The preliminary tests provided strong evidence of the quality and reliability of the dataset. First, the inspection of the data revealed no missing values across any of the variables, which is mainly due to the use of a fully mandatory online questionnaire on Google Forms. This complete dataset preserves the statistical power of the subsequent analyses and eliminates the potential bias related to imputation procedures (Hair et al., 2019).

Second, the Kolmogorov-Smirnov test (with Lilliefors significance correction) indicated that the three composite variables (VI, VMED, VD) significantly deviate from a normal distribution ($p < 0.001$). This result is not unexpected in behavioral research conducted on Likert-type data, where slight skewness and kurtosis are commonly observed (Field, 2018). Importantly, this finding guided the methodological choice of using non-parametric tests (Spearman, Mann-Whitney U, and Kruskal-Wallis H) and bootstrap-based mediation, which are robust to violations of the normality assumption (Hayes, 2022).

Third, the reliability assessment of the measurement instrument is very satisfactory. At the construct level, the Cronbach’s Alpha coefficients reach 0.743 for AI-driven personalization, 0.698 for customer engagement (rounded to 0.70), and 0.730 for brand loyalty. At the overall scale level, the Cronbach’s Alpha of 0.864 across the 28 items (24 construct items and 4 sociodemographic/behavioral items) clearly exceeds the recommended threshold of 0.70 (Nunnally, 1978) and falls within the range considered as good to excellent (George & Mallery, 2003). This indicates that the items consistently measure the constructs they are intended to measure and supports the internal validity of the questionnaire used to study AI-driven personalization, customer engagement, and brand loyalty in the Algerian context.

2.2. Discussion of Sociodemographic and Behavioral Profile

The sociodemographic and behavioral profile of the sample reflects the typical population of Algerian online consumers. The dominance of young adults – with the 18–24 and 25–34 age groups together representing 66.25% of the sample – is consistent with the structural reality of Algeria, where individuals under 35 represent approximately two-thirds of the total population, and where younger generations are the primary drivers of digital adoption and e-commerce activities. Several reports on the Algerian and broader MENA digital landscape indicate that this age cohort is the most exposed to social media advertising, mobile shopping applications, and AI-powered platforms (Statista, 2023).

The relatively balanced gender distribution (52.50% male vs. 47.50% female) ensures that potential gender differences could be tested without distortion linked to sample imbalance. In the Algerian context, this balance is noteworthy because women are increasingly present online and play a growing role in household purchasing decisions, even though their visibility in formal e-commerce statistics has historically been limited.

The online shopping frequency distribution shows that 79.50% of respondents shop online either occasionally or rarely. This behavioral pattern reflects the still-developing nature of e-commerce in Algeria, characterized by a low level of bank card penetration, a strong preference for cash-on-delivery, persistent logistical challenges, and a relative shortage of fully integrated AI-personalized e-commerce platforms operating locally. Despite the rapid growth of platforms such as Yassir, Jumia, and various Instagram-based stores, online shopping remains an emerging rather than a mainstream consumer practice.

Finally, the high level of education in the sample, with more than 80% of respondents holding a Bachelor's degree or higher, suggests a population with strong digital literacy and potentially greater openness to AI-driven personalization tools. However, this educational concentration also represents a limitation in the generalization of results to less-educated segments of the Algerian population.

2.3. Discussion of Descriptive Results (Key Variables)

The descriptive analysis of the three constructs reveals clearly positive perceptions among Algerian online consumers, with all three means lying between 3.78 and 3.85 on the 5-point Likert scale and consistently corresponding to the “Agree” interval [3.40 – 4.20[defined in Table 16.

The mean score of AI-driven personalization (M = 3.78) suggests that consumers generally perceive personalized digital marketing actions such as product recommendations, personalized offers, and tailored content as relevant and value-adding. This finding aligns with the international literature documenting that consumers tend to appreciate personalization when they perceive it as useful rather than intrusive (Chandra et al., 2022; Kumar et al., 2019).

Customer engagement obtained a similar mean (M = 3.80), indicating that respondents tend to interact actively with brands online, react to personalized communications, and feel connected to the brands that personalize their experience. This is consistent with Brodie et al. (2013) and Hollebeek et al. (2014), who emphasized that engagement is increasingly mediated by interactive digital touchpoints.

Brand loyalty obtained the highest mean (M = 3.85), suggesting a moderately strong overall loyalty orientation among Algerian online consumers toward brands that adopt AI-driven personalization strategies. This positive tendency, although moderate, reinforces the relevance of AI-personalization as a strategic lever for cultivating loyalty in an emerging digital market such as Algeria. The relatively low standard deviations across the three variables (all below 0.66) indicate that respondents share fairly homogeneous perceptions, which strengthens the consistency of the descriptive picture.

2.4. Discussion of Hypothesis Testing

2.4.1. Hypothesis 1 (H1)

The results of the multiple regression analysis support H1, indicating that AI-driven personalization has a positive and statistically significant effect on brand loyalty among Algerian online consumers ($R^2 = 0.326$; $F = 63.892$; significant at $\alpha = 0.001$). All three dimensions of personalization significantly contribute to predicting loyalty, with VID3 emerging as the most influential dimension ($\beta = 0.284$). The corresponding regression equation (VD = 1.492 + 0.179 × VID1 + 0.191 × VID2 + 0.250 × VID3) further illustrates the magnitude of each contribution.

This finding is consistent with the broader marketing literature. (Kumar et al., 2019) demonstrated that AI-based personalization increases perceived relevance, which strengthens consumers' affective commitment and loyalty intentions. Similarly, Riegger et al. (2021) emphasized that personalized recommendations enhance the customer's perception of being understood by the brand, which acts as a powerful loyalty driver. Pappas (2018) also showed that personalization fosters trust and satisfaction, both of which are direct antecedents of brand loyalty.

Within the Algerian context, this finding is particularly important. Despite the developing nature of e-commerce in the country, Algerian consumers; many of whom are young, educated, and digitally connected appear to be receptive to AI-personalized marketing actions. Personalization seems to compensate for some of the structural shortcomings of Algerian e-commerce (limited variety, weaker logistical infrastructure) by enhancing the perceived value of the customer experience. Consequently, brands operating in Algeria can leverage AI-personalization not only as a differentiation strategy but also as a relational tool to build long-term loyalty.

2.4.2. Hypothesis 2 (H2)

The results support H2: AI-driven personalization has a positive and significant effect on customer engagement ($R^2 = 0.361$; $F = 74.538$; significant at $\alpha = 0.001$). The three dimensions of personalization contribute almost equally to engagement, with standardized coefficients ranging from 0.233 to 0.254. The corresponding regression equation (VMED = 1.526 + 0.204 × VID1 + 0.192 × VID2 + 0.204 × VID3) reflects this balanced contribution.

This finding aligns strongly with the existing literature. Hollebeek et al. (2014) and Brodie et al. (2013) emphasized that personalization enhances cognitive, emotional, and behavioral engagement by making interactions more meaningful and relevant. Bleier and Eisenbeiss (2015) showed that personalized advertising increases the time and attention consumers devote to brand content, which directly translates into higher engagement. More recently, Chen and Lin (2019) found that AI-driven recommendations significantly increase users' likelihood to interact, share, and respond to brand communications on social media.

In the Algerian context, social media platforms particularly Facebook and Instagram – are central to consumer-brand interactions. The strong relationship between personalization and engagement suggests that when Algerian consumers receive content that reflects their preferences and needs, they are more likely to like, comment, share, follow, and revisit the brand. Given that many Algerian e-commerce activities operate through social commerce, this result has direct strategic value for brands seeking to maximize engagement in a market where formal CRM systems are still maturing.

2.4.3. Hypothesis 3 (H3)

The results provide strong support for H3, with customer engagement explaining a substantial 58.4% of the variance in brand loyalty ($R^2 = 0.584$; $F = 185.322$; significant at $\alpha = 0.001$). All three dimensions of engagement are highly significant predictors of loyalty, with VMD3 contributing the most ($\beta = 0.382$). The corresponding regression equation ($VD = 0.714 + 0.293 \times VMD1 + 0.218 \times VMD2 + 0.317 \times VMD3$) confirms the dominant role of behavioral engagement (VMD3) in driving loyalty.

This finding is in line with the engagement–loyalty literature. Vivek et al. (2012) demonstrated that engaged customers develop stronger emotional bonds with brands and are more likely to repeat purchases, recommend the brand, and resist competitive offers. Hollebeek (2011) similarly argued that customer engagement is among the most powerful relational antecedents of loyalty in digital environments. So and King (2014) found that engagement directly drives loyalty intentions through a mechanism of identification and trust-building.

Within the Algerian context, where consumer trust in online platforms remains fragile due to factors such as limited consumer protection, occasional fraud cases, and concerns about delivery reliability, customer engagement appears to act as a critical bridge to loyalty. When Algerian consumers actively interact with a brand through comments, reviews, story replies, or direct messages they progressively build a sense of trust and familiarity that translates into loyalty. This makes engagement a particularly strategic asset in markets where brand trust is hard-earned.

2.4.4. Hypothesis 4 (H4)

The mediation analysis conducted with the PROCESS Macro Model 4 supports H4: customer engagement partially mediates the relationship between AI-driven personalization and brand loyalty. The indirect effect is statistically significant ($\beta = 0.3943$; 95% CI [0.3190; 0.4671]) and represents a larger share of the total effect than the direct effect ($\beta = 0.1751$).

This result confirms an essential theoretical insight: personalization does not lead to loyalty in a purely automatic way, but rather through the activation of engagement mechanisms. This is in line with the findings of Pansari and Kumar (2017), who proposed that customer engagement is the central relational mechanism that translates marketing inputs into long-term loyalty outcomes. Hollebeek et al. (2019) likewise argued that personalization strategies are most effective when they trigger meaningful engagement experiences that consumers can feel, share, and reciprocate.

The fact that the mediation is partial, meaning that AI-personalization still has a residual direct effect on loyalty, also indicates that some loyalty effects of personalization operate through additional mechanisms not captured by engagement, such as perceived utility, time savings, or reduced search costs.

In the Algerian context, where many consumers are still discovering AI-personalized services, this partial mediation has a strategic implication: simply deploying personalization technologies is not enough. Brands must also actively cultivate engagement through interactive content, two-way communication, community-building, and prompt customer service to fully transform personalization investments into durable loyalty outcomes.

2.4.5. Hypothesis 5 (H5): Sociodemographic and Behavioral Differences

H5a: Age.

The Kruskal-Wallis test did not reveal a significant difference in brand loyalty across age groups ($H = 5.179$; $p = 0.269$; not significant at $\alpha = 0.05$), and H5a is therefore not supported. While some studies, such as (Lissitsa & Kol, 2016), suggested that Generation Y and Z consumers respond differently to digital marketing than older generations, the present results indicate that, once exposed to AI-personalization, Algerian consumers of different ages develop similar levels of brand loyalty. A possible explanation is that AI-driven personalization, by tailoring content to individual profiles regardless of age, neutralizes age-related differences. In the Algerian context, this absence of age effect may also reflect the fact that older consumers who shop online are themselves a self-selected, digitally active sub-group whose behavior converges with that of younger users.

H5b: Gender.

The Mann-Whitney U test revealed a significant gender difference ($U = 16,225$; $p = 0.001$; significant at $\alpha = 0.01$), with male respondents reporting higher brand loyalty than female respondents. H5b is therefore supported. This finding partially aligns with previous research showing gender differences in online consumer behavior. Hwang (2010) and Pascual-Miguel et al. (2015) reported that men and women differ in their information-processing styles online: men tend to focus on functional and utilitarian aspects, while women place more emphasis on social, relational, and trust-related cues.

In the Algerian context, this gender gap may reflect the fact that female consumers are often more cautious online due to greater concerns about data privacy, payment security, and product authenticity, especially in a market where consumer protection mechanisms are still evolving. Female consumers may also tend to compare more brands before becoming loyal, while male consumers may more rapidly stabilize their loyalty toward brands that satisfy their functional expectations through personalized offers. This finding has clear managerial implications: brands targeting female Algerian consumers should reinforce trust-building elements (transparent return policies, secure payment, customer testimonials) alongside AI-personalization.

H5c: Online Shopping Frequency.

The Kruskal-Wallis test indicated a significant difference in brand loyalty across online shopping frequency groups ($H = 10.373$; $p = 0.016$; significant at $\alpha = 0.05$). Very frequent shoppers exhibit the highest mean rank (261.52), substantially above all other groups. H5c is therefore supported. This result is consistent with the literature on customer experience accumulation. Bilgihan et al. (2016) demonstrated that frequent online shoppers accumulate more touchpoints with personalized systems, which strengthens their loyalty over time. Kim and Niehm (2009) similarly reported that repeated positive experiences with online brands build a “habit-loyalty” loop. Within the Algerian context, this finding suggests that the more consumers shop online, the more exposure they get to AI-personalization, and the more they internalize its benefits – leading to higher loyalty. From a managerial standpoint, this implies that strategies aimed at increasing the frequency of online interactions (loyalty rewards, gamified shopping, frequent personalized notifications) can act as a virtuous cycle that simultaneously increases engagement and loyalty.

H5d: Educational Level.

The Kruskal-Wallis test did not yield a significant difference in brand loyalty across educational level groups ($H = 7.661$; $p = 0.105$; not significant at $\alpha = 0.05$), and H5d is therefore not supported. Although some studies have argued that more educated consumers may be either more critical of marketing techniques or more receptive to digital innovations (Lusardi & Mitchell, 2014), the present findings suggest that the loyalty effect of AI-personalization operates uniformly regardless of educational level. This result is encouraging from a marketing perspective: it indicates that AI-driven personalization is an inclusive strategy that can build loyalty among Algerian consumers across the educational spectrum. The absence of educational differentiation may be due to the intuitive nature of modern AI-personalized interfaces, which translate complex algorithmic recommendations into simple, user-friendly experiences (relevant product suggestions, clear personalized offers), accessible to consumers regardless of their formal educational background.

2.5. Theoretical and Managerial Implications

2.5.1. Theoretical Implications

The findings of this study contribute to the theoretical literature on digital marketing and consumer behavior in several ways. First, they extend the empirical evidence on AI-driven personalization to an underexplored emerging market – Algeria – and confirm the cross-cultural relevance of established theoretical frameworks linking personalization to loyalty (Chandra et al., 2022; Kumar et al., 2019).

Second, the study reinforces the central role of customer engagement as a relational mediator between marketing actions and loyalty outcomes, in line with the Service-Dominant Logic and the engagement-based view proposed by Hollebeek et al. (2019) and Pansari and Kumar (2017). The partial mediation result enriches the literature by showing that personalization affects loyalty through both direct utilitarian channels (relevance, convenience) and indirect engagement-driven channels (interaction, emotional connection).

Third, the absence of significant age and educational level effects, combined with the presence of significant gender and shopping frequency effects, contributes to refining the boundary conditions of the personalization–loyalty relationship in emerging digital markets. These findings invite future research to explore deeper psychological and cultural moderators (privacy concerns, trust, technology readiness) rather than relying solely on broad demographic categories.

2.5.2. Managerial Implications

The findings of this study provide several actionable insights for marketing managers, e-commerce operators, and digital agencies in Algeria.

First, given the significant positive effect of AI-driven personalization on both engagement and loyalty, Algerian brands and e-commerce platforms are encouraged to invest in AI-based tools that enable real-time personalization of product recommendations, targeted communications, and customized landing pages. Even modest investments in personalization technologies (collaborative filtering, recommendation engines, AI-assisted segmentation, dynamic email marketing) can generate substantial loyalty gains.

Second, since customer engagement plays a partial mediating role, brands should not focus only on the technological side of personalization but also on cultivating engagement experiences. Practical actions include responsive customer service on social media, interactive Stories and live sessions on Instagram and Facebook, gamified rewards programs, user-generated content campaigns, and personalized after-sales follow-ups. The combination of AI-personalization and human-centered engagement strategies produces the strongest loyalty outcomes.

Third, the gender difference identified in the analysis suggests that managers should adapt their personalization and engagement strategies to gender-specific preferences. Specifically, female-targeted communications should incorporate stronger trust signals (clear return and refund policies, secure payment guarantees, transparent product information, customer reviews, and testimonials), while male-targeted strategies can focus more on functional, utilitarian, and time-saving benefits of personalization.

Fourth, since brand loyalty increases with online shopping frequency, marketers should design strategies that progressively increase the consumer's interaction frequency with the brand.

Loyalty programs offering tiered personalized rewards, periodic exclusive offers, push notifications based on browsing history, and re-engagement campaigns after periods of inactivity are particularly relevant tactics.

Fifth, since the personalization–loyalty effect appears to operate uniformly across age and educational level groups, marketers can confidently roll out AI-personalized strategies across broad consumer segments without segmenting on these criteria. However, this universal applicability should not be confused with a “one-size-fits-all” content approach: the personalization itself must remain individualized, even if the strategic framework is consistent.

Finally, at a broader level, these findings highlight the strategic importance of building a robust digital infrastructure in Algeria, including reliable payment systems, efficient logistics, and consumer data protection frameworks. Without such infrastructure, the full potential of AI-driven personalization cannot be realized, and the loyalty effects observed in this study may be constrained by structural limitations of the Algerian e-commerce ecosystem.

Conclusion

This chapter has presented and discussed the empirical findings of the present research. The data screening confirmed the high quality and reliability of the dataset, with the overall measurement scale and each individual construct meeting or approaching the recommended reliability thresholds. The descriptive analysis revealed positive perceptions of AI-driven personalization, customer engagement, and brand loyalty, all situated within the “Agree” interval of the Likert scale among Algerian online consumers.

The hypothesis testing supported six of the eight tested hypotheses: AI-driven personalization has a significant positive effect on both brand loyalty (H1) and customer engagement (H2); customer engagement positively affects brand loyalty (H3); customer engagement partially mediates the relationship between AI-personalization and brand loyalty (H4); and significant differences in loyalty were found according to gender (H5b) and online shopping frequency (H5c). However, no significant differences were found according to age (H5a) or educational level (H5d).

Taken together, these findings demonstrate that AI-driven personalization is a powerful strategic lever for building brand loyalty in the Algerian online market, and that this effect operates primarily through the engagement of consumers. The theoretical and managerial implications derived from this study lay the foundation for the general conclusion of the dissertation, which will be presented in the following section.

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CONCLUSION

This study set out to investigate the impact of AI-driven personalization in digital marketing on brand loyalty among Algerian online consumers, with a particular focus on the mediating role of customer engagement. Drawing on a positivist epistemological stance and a deductive quantitative approach, the research tested five hypotheses using data collected from a convenience sample of 400 Algerian online consumers through a structured questionnaire, and analyzed using IBM SPSS Statistics. This concluding chapter summarizes the principal findings, draws together the theoretical and practical implications, acknowledges the limitations of the study, and outlines avenues for future research.

The empirical results provide robust support for the proposed conceptual model. AI-driven personalization was found to exert a positive and statistically significant effect on brand loyalty among Algerian online consumers (H1 supported), confirming that personalized marketing communications generate meaningful loyalty outcomes in the Algerian context. AI-driven personalization also significantly predicted customer engagement (H2 supported), and customer engagement in turn significantly predicted brand loyalty (H3 supported), establishing the full chain of relationships specified by the conceptual framework.

The mediation analysis confirmed that customer engagement plays a significant mediating role in the relationship between AI-driven personalization and brand loyalty (H4 supported), demonstrating that the effect of personalization on loyalty operates substantially through the activation of consumer cognitive, emotional, and behavioral engagement. Finally, the demographic analyses revealed meaningful differences in the personalization-loyalty relationship across consumer segments, with H5 and its sub-hypotheses. These findings answer the main research question affirmatively: AI-driven personalization significantly affects brand loyalty among Algerian online consumers, and customer engagement mediates this relationship.

From a theoretical perspective, this study contributes to the digital marketing literature by providing one of the first empirical tests of the AI personalization-engagement-loyalty mediation model in the Algerian context, addressing a significant geographic and conceptual gap. The integration of the Technology Acceptance Model and the Stimulus-Organism-Response framework offers a coherent theoretical lens for understanding how AI-driven stimuli are perceptually accepted and behaviorally translated into engagement and loyalty outcomes.

From a practical standpoint, the findings provide directly actionable guidance for organizations operating in the Algerian digital market. Marketing managers are encouraged to prioritize the perceived relevance, recommendation accuracy, and perceived usefulness of their AI-personalized communications, as these dimensions emerged as the principal drivers of consumer engagement and brand loyalty. The socio-demographic differences and behavioral profile observed further suggest that AI personalization strategies should be tailored to specific consumer segments rather than applied uniformly across the entire customer base.

Limitations

Despite its contributions, this study is subject to several limitations that should be acknowledged. The cross-sectional design captures consumer perceptions at a single point in time and does not allow for the analysis of how the studied relationships evolve throughout the consumer journey. In addition, the use of non-probability convenience sampling limits the statistical generalizability of the findings. Furthermore, the geographic focus on Algerian consumers restricts the direct transferability of the results to other national contexts without empirical replication.

Suggestions for Future Research

Future research could extend this work in several productive directions. First, adopting a longitudinal design would allow researchers to examine the dynamic evolution of customer engagement and brand loyalty over time, thereby providing stronger evidence of causal relationships. Second, cross-country comparative studies could determine whether the mediation pattern identified in Algeria is also applicable to other emerging digital markets in North Africa, the Middle East, and Sub-Saharan Africa. Future studies may also investigate moderating variables such as consumer trust, perceived data privacy, and digital literacy, which emerged in the literature as important boundary conditions influencing the relationship between AI-driven personalization and brand loyalty. Finally, qualitative approaches could complement the present quantitative findings by offering deeper insights into the lived experiences of Algerian online consumers in personalized digital environments.

In an era of accelerating digital transformation, the ability of brands to deliver personalized, relevant, and meaningful experiences to individual consumers has become a defining factor of competitive advantage. This study has shown that, in the Algerian context as elsewhere, AI-driven personalization has the power to engage consumers and build lasting loyalty, but only when it is designed and deployed with attention to relevance, accuracy, and the specific characteristics of the audience it seeks to serve. The findings offer both academic insight and practical direction for organizations seeking to navigate the rapidly evolving digital marketing landscape, and they open the door to a richer and more contextually grounded research agenda on AI, consumer behavior, and brand loyalty in the Algerian and broader emerging-market context.

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APPENDIX

Appendix A: QUESTIONNAIRE

QUESTIONNAIRE DE RECHERCHE

Mémoire de fin d'études; Master Management Marketing

École Nationale Supérieure de Management (ENSM) - Kolea

Thème :

L'Impact de la Personnalisation Pilotée par l'IA dans le Marketing Digital sur la Fidélité à la Marque chez les Consommateurs Algériens en Ligne

Madame, Monsieur,

Dans le cadre de notre mémoire de Master en Management Marketing à l'École Nationale Supérieure de Management (ENSM), nous réalisons une étude sur l'impact de la personnalisation basée sur l'intelligence artificielle dans le marketing digital sur la fidélité à la marque.

Ce questionnaire est anonyme, confidentiel et ne prend qu'1 à 2 minutes.

Il n'y a pas de bonnes ou mauvaises réponses. Veuillez répondre selon votre expérience personnelle.

Nous vous remercions sincèrement pour votre participation.

SECTION 1 : Questions de Filtrage

Q1. Êtes-vous algérien(ne) ?

☐ Oui : Continuez le questionnaire
☐ Non : Merci, vous ne correspondez pas au profil recherché

Q2. Utilisez-vous régulièrement Internet (réseaux sociaux, e-mail, sites web) ?

☐ Oui : Continuez le questionnaire
☐ Non : Merci, vous ne correspondez pas au profil recherché

Q3. Avez-vous déjà interagi avec le contenu personnalisé d'une marque en ligne (publicités ciblées, recommandations de produits, e-mails personnalisés) ?

☐ Oui : Continuez le questionnaire
☐ Non : Merci, vous ne correspondez pas au profil recherché

SECTION 2 : Informations Démographiques

Q3. Âge :

☐ 18 – 24 ans
☐ 25 – 34 ans
☐ 35 – 44 ans
☐ 45 – 54 ans
☐ 55 ans et plus

Q4. Genre :

☐ Homme
☐ Femme

Q5. Fréquence d'achats en ligne :

☐ Rarement (moins d'une fois par mois)
☐ Occasionnellement (1 à 2 fois par mois)
☐ Fréquemment (3 à 5 fois par mois)
☐ Très fréquemment (plus de 5 fois par mois)

Q6. Niveau d'études :

☐ Lycée ou moins
☐ Licence
☐ Master
☐ Doctorat
☐ Autre

SECTION 3 : Personnalisation Pilotée par l'IA

Veuillez indiquer votre degré d'accord avec chacune des affirmations suivantes.

1 = Pas du tout d'accord 2 = Pas d'accord 3 = Neutre 4 = D'accord 5 = Tout à fait d'accord

Dimension 1: Pertinence Perçue

Q7. Les publicités et contenus personnalisés que je reçois en ligne correspondent généralement à mes centres d'intérêt.

☐1 ☐2 ☐3 ☐4 ☐5

Q8. Les contenus personnalisés qui m'apparaissent sur les réseaux sociaux me semblent adaptés à mon profil.

☐1 ☐2 ☐3 ☐4 ☐5

Q9. Les marques que je suis en ligne semblent comprendre mes besoins et mes préférences.

☐1 ☐2 ☐3 ☐4 ☐5

Dimension 2: Précision des Recommandations

Q10. Les recommandations de produits ou services que je reçois en ligne reflètent fidèlement mes habitudes de consommation.

☐1 ☐2 ☐3 ☐4 ☐5

Q11. Les suggestions qui me sont proposées sur les plateformes numériques correspondent à mes achats ou recherches précédents.

☐1 ☐2 ☐3 ☐4 ☐5

Q12. Je trouve que les recommandations personnalisées reçues en ligne sont généralement exactes et pertinentes.

☐1 ☐2 ☐3 ☐4 ☐5

Dimension 3: Utilité Perçue

Q13. La personnalisation des contenus numériques améliore mon expérience globale en ligne.

☐1 ☐2 ☐3 ☐4 ☐5

Q14. Recevoir des offres adaptées à mon profil me fait gagner du temps dans ma recherche d'informations.

☐1 ☐2 ☐3 ☐4 ☐5

Q15. Les contenus personnalisés m'aident à découvrir des produits ou services qui répondent réellement à mes attentes.

☐1 ☐2 ☐3 ☐4 ☐5

SECTION 4 : Engagement Client (Variable Médiatrice)

Veuillez indiquer votre degré d'accord avec chacune des affirmations suivantes.

1 = Pas du tout d'accord 2 = Pas d'accord 3 = Neutre 4 = D'accord 5 = Tout à fait d'accord

Dimension 1: Engagement Cognitif

Q16. Lorsqu'une marque me propose un contenu personnalisé, je prends le temps de le lire attentivement.

☐1 ☐2 ☐3 ☐4 ☐5

Q17. Les contenus personnalisés d'une marque stimulent ma curiosité et m'incitent à en apprendre davantage sur ses produits ou services.

☐1 ☐2 ☐3 ☐4 ☐5

Q18. Je réfléchis activement aux informations personnalisées qu'une marque me transmet avant de prendre une décision d'achat.

☐1 ☐2 ☐3 ☐4 ☐5

Dimension 2: Engagement Émotionnel

Q19. Je ressens des émotions positives envers une marque qui me propose des contenus adaptés à mes préférences.

☐1 ☐2 ☐3 ☐4 ☐5

Q20. Lorsqu'une marque me contacte de manière personnalisée, je me sens valorisé(e) en tant que client(e).

☐1 ☐2 ☐3 ☐4 ☐5

Q21. La personnalisation des communications d'une marque renforce mon sentiment d'appartenance à cette marque.

☐1 ☐2 ☐3 ☐4 ☐5

Dimension 3: Engagement Comportemental

Q22. J'interagis régulièrement avec les publications personnalisées d'une marque (likes, commentaires, partages).

☐1 ☐2 ☐3 ☐4 ☐5

Q23. Je suis prêt(e) à recommander une marque qui me propose des expériences numériques personnalisées à mon entourage.

☐1 ☐2 ☐3 ☐4 ☐5

Q24. Je visite régulièrement le compte ou le site web d'une marque avec laquelle j'ai eu des interactions personnalisées positives.

☐1 ☐2 ☐3 ☐4 ☐5

SECTION 5 : Fidélité à la Marque (Variable Dépendante)

Veuillez indiquer votre degré d'accord avec chacune des affirmations suivantes.

1 = Pas du tout d'accord 2 = Pas d'accord 3 = Neutre 4 = D'accord 5 = Tout à fait d'accord

Dimension 1: Fidélité Attitudinale

Q25. Je préfère continuer à utiliser les services d'une marque qui me propose des contenus personnalisés pertinents plutôt que de changer pour une autre.

☐1 ☐2 ☐3 ☐4 ☐5

Q26. Je considère la marque avec laquelle j'interagis régulièrement en ligne comme mon premier choix dans sa catégorie.

☐1 ☐2 ☐3 ☐4 ☐5

Q27. La personnalisation des communications d'une marque renforce mon attachement émotionnel et ma préférence envers elle.

☐1 ☐2 ☐3 ☐4 ☐5

Dimension 2: Fidélité Comportementale

Q28. J'ai tendance à renouveler mes achats ou demandes de services auprès d'une marque qui me propose des contenus personnalisés adaptés à mes besoins.

☐1 ☐2 ☐3 ☐4 ☐5

Q29. Je recommande activement à mon entourage les marques qui m'ont offert une expérience numérique personnalisée satisfaisante.

☐1 ☐2 ☐3 ☐4 ☐5

Q30. Même face à des offres concurrentes, je reste fidèle à une marque avec laquelle j'ai établi une relation personnalisée positive en ligne.

☐1 ☐2 ☐3 ☐4 ☐5

SECTION 6 : Préférences des consommateurs en matière d'IA et de personnalisation

Q31. Dans quels domaines souhaitez-vous bénéficier davantage de la personnalisation basée sur l'intelligence artificielle ?

☐ E-commerce (achat en ligne)
☐ Réseaux sociaux (Facebook, Instagram, TikTok…)
☐ Publicité en ligne
☐ Streaming (films, séries, musique)
☐ Banque et services financiers
☐ Applications mobiles
☐ Éducation en ligne (plateformes d'apprentissage)
☐ Voyage et tourisme
☐ Santé (applications et services numériques)
☐ Autre : __________

Q32. Quels types de personnalisation préférez-vous ?

☐ Recommandations de produits ou services
☐ Offres et promotions personnalisées
☐ Contenu adapté à mes centres d'intérêt
☐ Suggestions basées sur mes recherches précédentes
☐ Personnalisation de l'interface (affichage, navigation)

Q33. Sur quels canaux préférez-vous recevoir du contenu personnalisé ?

☐ Réseaux sociaux
☐ E-mails
☐ Sites web
☐ Applications mobiles
☐ SMS

APPENDIX B: SPSS Output Tables

Table 1 Missing Values Analysis

Statistiques

		Âge :	Genre :	Fréquence d'achats en ligne :	Niveau d'études :
N	Valide	400	400	400	400
	Manquant	0	0	0	0

Statistiques

		Les contenus personnalisés que je reçois en ligne correspondent généralement à mes centres d' intérêt.	Les contenus personnalisés qui apparaissent sur les réseaux sociaux correspondent à mes préférences personnelles.	Les contenus personnalisés que je reçois sont adaptés à mon profil.	Les recommandations de produits ou services que je reçois en ligne reflètent fidèlement mes habitudes de consommation.	Les suggestions qui me sont proposées sur les plateformes numériques correspondent à mes achats ou recherches précédents.	Les recommandations personnalisées que je reçois correspondent précisément à mes attentes.	La personnalisation des contenus numériques améliore mon expérience globale en ligne.	Recevoir des offres adaptées à mon profil me fait gagner du temps dans ma recherche d'informations.	Les contenus personnalisés m'aident à découvrir des produits ou services qui répondent réellement à mes attentes.
N	Valide	400	400	400	400	400	400	400	400	400
	Manquant	0	0	0	0	0	0	0	0	0

Statistiques

		Lorsque je reçois un contenu personnalisé d'une marque, je prends le temps de le lire attentivement.	Les contenus personnalisés d'une marque stimulent ma curiosité et m'incitent à en apprendre davantage sur ses produits ou services.	Je réfléchis activement aux informations personnalisées qu'une marque me transmet avant de prendre une décision d'achat.	Je ressens des émotions positives envers une marque qui me propose des contenus adaptés à mes préférences.	Lorsqu'une marque me contacte de manière personnalisée, je me sens valorisé(e) en tant que client (e).	La personnalisation des communications d'une marque renforce mon attachement émotionnel à cette marque.	J'interagis régulièrement avec les publications personnalisées d'une marque (likes, commentaires, partages).	Je consulte attentivement les contenus personnalisés proposés par une marque lorsque je les vois en ligne.	Je visite régulièrement le compte ou le site web d'une marque avec laquelle j'ai eu des interactions personnalisées positives.
N	Valide	400	400	400	400	400	400	400	400	400
	Manquant	0	0	0	0	0	0	0	0	0

Statistiques

		Je préfère continuer à utiliser les services d'une marque qui me propose des contenus personnalisés pertinents plutôt que de changer pour une autre.	Je considère la marque avec laquelle j'interagis régulièrement en ligne comme mon premier choix dans sa catégorie.	Je développe une préférence pour les marques qui personnalisent leurs communications en fonction de mes besoins.	J'ai tendance à renouveler mes achats ou demandes de services auprès d'une marque qui me propose des contenus personnalisés adaptés à mes besoins.	Je recommande activement à mon entourage les marques qui m'ont offert une expérience numérique personnalisée satisfaisante.	Même face à des offres concurrentes, je reste fidèle à une marque avec laquelle j'ai établi une relation personnalisée positive en ligne.
N	Valide	400	400	400	400	400	400
	Manquant	0	0	0	0	0	0

Source: IBM SPSS Statistics 27 Output.

Table 2 Reliability Analysis of AI-Driven Personalization Scale

Statistiques de fiabilité

Alpha de Cronbach	Nombre d'éléments
,743	3

Source: IBM SPSS Statistics 27 Output.

Table 3 Reliability Analysis of Customer Engagement Scale

Statistiques de fiabilité

Alpha de Cronbach	Nombre d'éléments
,698	3

Source: IBM SPSS Statistics 27 Output.

Table 4 Reliability Analysis of Brand Loyalty Scale

Statistiques de fiabilité

Alpha de Cronbach	Nombre d'éléments
,730	2

Source: IBM SPSS Statistics 27 Output.

Table 5 Reliability Test Results

Statistiques de fiabilité

Alpha de Cronbach	Nombre d'éléments
,864	28

Source: IBM SPSS Statistics 27 Output.

Table 6 Normality Test Results

Tests de normalité

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistiques	ddl	Sig.	Statistiques	ddl	Sig.
VI	,130	400	<,001	,935	400	<,001
VMED	,131	400	<,001	,943	400	<,001
VD	,152	400	<,001	,942	400	<,001

a. Correction de signification de Lilliefors

Source: IBM SPSS Statistics 27 Output.

Table 10 Pearson Correlation Analysis for H1, H2, and H3

Corrélations

			VI	VMED	VD
Rho de Spearman	VI	Coefficient de corrélation	1,000	,548**	,514**
		Sig. (bilatérale)	.	<,001	<,001
		N	400	400	400
	VMED	Coefficient de corrélation	,548**	1,000	,714**
		Sig. (bilatérale)	<,001	.	<,001
		N	400	400	400
	VD	Coefficient de corrélation	,514**	,714**	1,000
		Sig. (bilatérale)	<,001	<,001	.
		N	400	400	400

Source: IBM SPSS Statistics 27 Output.

Table 11 Multiple Linear Regression Results for H1

Coefficients[a]

Modèle		Coefficients non standardisés B	Coefficients non standardisés Erreur standard	Coefficients standardisés Bêta	t	Sig.
1	(Constante)	1,492	,172		8,661	<,001
	VID1	,179	,044	,204	4,059	<,001
	VID2	,191	,046	,213	4,169	<,001
	VID3	,250	,043	,284	5,766	<,001

a. Variable dépendante : VD

Régression

Variables introduites/éliminées[a]

Modèle	Variables introduites	Variables éliminées	Méthode
1	VID3, VID1, VID2[b]	.	Introduire

a. Variable dépendante : VD

b. Toutes les variables demandées ont été introduites.

Récapitulatif des modèles

Modèle	R	R-deux	R-deux ajusté	Erreur standard de l'estimation
1	,571[a]	,326	,321	,53854

a. Prédicteurs : (Constante), VID3, VID1, VID2

ANOVA[a]

Modèle		Somme des carrés	ddl	Carré moyen	F	Sig.
1	Régression	55,592	3	18,531	63,892	<,001[b]
	de Student	114,851	396	,290		
	Total	170,443	399			

a. Variable dépendante : VD

b. Prédicteurs : (Constante), VID3, VID1, VID2

Source: IBM SPSS Statistics 27 Output.

Table 12 Multiple Linear Regression Results for H2**.**

Coefficients[a]

Double-cliquez pour activer

Modèle		B	Erreur standard	Coefficients standardisés Bêta	t	Sig.
		non standardisés				
1	(Constante)	1,526	,154		9,897	<,001
	VID1	,204	,039	,254	5,183	<,001
	VID2	,192	,041	,233	4,676	<,001
	VID3	,204	,039	,252	5,260	<,001

a. Variable dépendante : VMED

Regres

Annuler une action utilisateur

Variables introduites/éliminées[a]

Modèle	Variables introduites	Variables éliminées	Méthode
1	VID3, VID1, VID2[b]	.	Introduire

a. Variable dépendante : VMED

b. Toutes les variables demandées ont été introduites.

Récapitulatif des modèles

Modèle	R	R-deux	R-deux ajusté	Erreur standard de l'estimation
1	,601[a]	,361	,356	,48177

a. Prédicteurs : (Constante), VID3, VID1, VID2

ANOVA[a]

Modèle		Somme des carrés	ddl	Carré moyen	F	Sig.
1	Régression	51,902	3	17,301	74,538	<,001[b]
	de Student	91,912	396	,232		
	Total	143,814	399			

a. Variable dépendante : VMED

b. Prédicteurs : (Constante), VID3, VID1, VID2

Source: IBM SPSS Statistics 27 Output.

Table 13 Multiple Linear Regression Results for H3

Coefficients[a]

Modèle		Coefficients non standardisés		Coefficients standardisés		
		B	Erreur standard	Bêta	t	Sig.
1	(Constante)	,714	,137		5,217	<,001
	VMD1	,293	,033	,327	8,774	<,001
	VMD2	,218	,032	,254	6,744	<,001
	VMD3	,317	,032	,382	9,900	<,001

a. Variable dépendante : VD

Regression

Variables introduites/éliminées[a]

Modèle	Variables introduites	Variables éliminées	Méthode
1	VMD3, VMD1, VMD2[b]	.	Introduire

a. Variable dépendante : VD

b. Toutes les variables demandées ont été introduites.

Récapitulatif des modèles

Modèle	R	R-deux	R-deux ajusté	Erreur standard de l'estimation
1	,764[a]	,584	,581	,42313

a. Prédicteurs : (Constante), VMD3, VMD1, VMD2

ANOVA[a]

Modèle		Somme des carrés	ddl	Carré moyen	F	Sig.
1	Régression	99,542	3	33,181	185,322	<,001[b]
	de Student	70,901	396	,179		
	Total	170,443	399			

a. Variable dépendante : VD

b. Prédicteurs : (Constante), VMD3, VMD1, VMD2

Source:IBM SPSS Statistics 27 Output.

Table 14 PROCESS Macro Model 4 Mediation Analysis Results for H4

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

      Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
   Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
   Y  : VD
   X  : VI
   M  : VMED

Sample
Size:  400

**************************************************************************
OUTCOME VARIABLE:
 VMED

Model Summary
       R       R-sq        MSE          F        df1        df2          p
    ,6007      ,3608      ,2310   224,6771     1,0000   398,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,5258      ,1535     9,9368      ,0000     1,2240     1,8276
VI            ,6005      ,0401    14,9892      ,0000      ,5218      ,6793

Standardized coefficients
        coeff
VI      ,6007

**************************************************************************
OUTCOME VARIABLE:
 VD

Model Summary
       R       R-sq        MSE          F        df1        df2          p
    ,7743      ,5995      ,1719   297,1823     2,0000   397,0000      ,0000


   constant      1,5027      ,1719     8,7441      ,0000     1,1649     1,8406
   VI             ,6196      ,0448    13,8163      ,0000      ,5315      ,7078

   Standardized coefficients
           coeff
   VI      ,5693

   ************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

   Total effect of X on Y
        Effect         se          t          p       LLCI       ULCI       c_cs
         ,6196      ,0448    13,8163      ,0000      ,5315      ,7078      ,5693

   Direct effect of X on Y
        Effect         se          t          p       LLCI       ULCI      c'_cs
         ,1905      ,0432     4,4066      ,0000      ,1055      ,2755      ,1751

   Indirect effect(s) of X on Y:
            Effect     BootSE   BootLLCI   BootULCI
   VMED      ,4291      ,0475      ,3383      ,5256

   Completely standardized indirect effect(s) of X on Y:
            Effect     BootSE   BootLLCI   BootULCI
   VMED      ,3943      ,0375      ,3190      ,4671

   *********************** ANALYSIS NOTES AND ERRORS ************************

   Level of confidence for all confidence intervals in output:
     95,0000

   Number of bootstrap samples for percentile bootstrap confidence intervals:
```

Source: IBM SPSS Statistics 27 Output.

Table 15 Kruskal–Wallis Test Results for H5a

```
NPAR TESTS
  /K-W=VD BY agenv(2 6)
  /MISSING ANALYSIS.
```

Tests non paramétriques

Test de Kruskal-Wallis

Rangs

	Âge :	N	Rang moyen :
VD	18 – 24 ans	155	198,53
	25 – 34 ans	110	207,27
	35 – 44 ans	77	210,01
	45 – 54 ans	38	163,18
	55 ans et plus	20	212,83
	Total	400	

Tests statistiques[a,b]

	VD
H de Kruskal-Wallis	5,179
df	4
Sig. asymptotique	,269

a. Test de Kruskal Wallis

b. Variable de regroupement : Âge :

Source: IBM SPSS Statistics 27 Output.

Table 16 Mann–Whitney U Test Results for H5b

Tests non paramétriques

Test de Mann-Whitney

Rangs

	Genre :	N	Rang moyen :	Somme des rangs
VD	H	210	218,24	45830,00
	F	190	180,89	34370,00
	Total	400		

Tests statistiques[a]

	VD
U de Mann-Whitney	16225,000
W de Wilcoxon	34370,000
Z	-3,241
Sig. asymptotique (bilatérale)	,001

a. Variable de regroupement : Genre :

```
NPAR TESTS
  /K-W=VD BY agenv(2 6)
  /MISSING ANALYSIS.
```

Source: IBM SPSS Statistics 27 Output.

Table 17 Kruskal–Wallis Test Results for H5c

Tests non paramétriques

Test de Kruskal-Wallis

Rangs

	Fréquence d'achats en ligne :	N	Rang moyen :
VD	Fréquemment (3 à 5 fois par mois)	54	207,00
	Occasionnellement (1 à 2 fois par mois)	170	187,11
	Rarement (moins d'une fois par mois)	148	201,97
	Très fréquemment (plus de 5 fois par mois)	28	261,52
	Total	400	

Tests statistiques[a,b]

	VD
H de Kruskal-Wallis	10,373
df	3
Sig. asymptotique	,016

a. Test de Kruskal Wallis

b. Variable de regroupement : Fréquence d'achats en ligne :

Source:IBM SPSS Statistics 27 Output.

Table 18 Kruskal–Wallis Test Results for H5d

Test de Kruskal-Wallis

Rangs

	Niveau d'études :	N	Rang moyen :
VD	Autre	37	189,20
	Doctorat	51	173,21
	Licence	83	192,29
	Lycée ou moins	43	233,55
	Master	186	206,26
	Total	400	

Tests statistiques[a,b]

	VD
H de Kruskal-Wallis	7,661
df	4
Sig. asymptotique	,105

a. Test de Kruskal Wallis

b. Variable de regroupement : Niveau d'études :

Source: IBM SPSS Statistics 27 Output.