Beyond Functionality: The Role of AI-Driven Personalization in User Retention of Mobile Applications

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Abstract

This study investigates the factors influencing users' intention to continue using artificial intelligence (AI) mobile applications. By extending the Expectation–Confirmation Model (ECM), personalization is incorporated as a central variable. Adopting a quantitative approach, data were collected from 300 users of AI mobile applications, and the statistical analysis was conducted using SPSS 20 and Smart PLS 4.

The findings confirm that satisfaction, perceived usefulness, and personalization are significant predictors of continuous usage intention. Expectation confirmation with regard to AI applications positively influences both perceived usefulness and user satisfaction. Moreover, perceived usefulness exerts a significant and positive effect on satisfaction.

This research advances the literature by highlighting the pivotal role of personalization in driving adoption and user loyalty within AI mobile applications. For developers and managers, the results suggest that integrating tailored personalization features can enhance user retention by fostering individualized experiences.

The originality of this study lies in the integration of personalization into the ECM framework, offering a more nuanced understanding of user retention mechanisms in the specific context of AI mobile applications.

Keywords: Expectation–Confirmation Model (ECM), Artificial Intelligence (AI), Mobile Applications, Personalization, Perceived Usefulness, Satisfaction, Continuous Usage Intention.

Introduction

Mobile applications and artificial intelligence (AI) have emerged as central drivers of technological innovation, reshaping the ways in which users interact with digital systems. A mobile application can be defined as "software designed to operate on mobile devices such as smartphones and tablets, offering personalized and accessible services" (Bhave et al., 2013). When combined with AI, these digital tools significantly enhance the user experience. AI itself has been described as "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019). This definition underscores AI's adaptive and evolutionary capacity in processing data.

In marketing, AI has further been conceptualized as "a method of leveraging customer data to anticipate the customer's next move and improve their journey. AI bridges the gap between data science and execution by filtering and analyzing vast amounts of data" (Abi et al., 2021). These perspectives highlight AI's versatility across multiple domains. The rapid evolution of AI techniques in recent years, particularly within mobile computing (Sarker et al., 2020; Kashive & Powale, 2020), has enabled smartphones to host mobile applications that operate with increasing intelligence and intuitiveness. AI can be applied to structured, semi-structured, and unstructured data to optimize application performance. Popular approaches include machine learning (ML), deep learning (DL), natural language processing (NLP), and expert systems (ES), all of which empower mobile applications to deliver personalized services tailored to users' specific needs.

The existing literature particularly the Expectation–Confirmation Model (ECM) developed by Bhattacherjee (2001) emphasizes the critical role of satisfaction, perceived usefulness, and expectation confirmation in the adoption and continuous use of information systems. Derived from expectation–confirmation theory (ECT) and the technology acceptance model (TAM), ECM highlights how users' initial expectations shape their subsequent perceptions of usefulness and satisfaction following technology use. More recent studies demonstrate that personalization, enabled by AI, plays a crucial role in shaping both adoption and continuous usage intentions of mobile applications (Kumar et al., 2019; Ameen et al., 2021).

Nevertheless, despite significant advances in the integration of AI within mobile applications, an essential research question remains: ***How can AI-powered mobile applications optimize user satisfaction and continuous usage intention by accounting for personalization, perceived usefulness, and expectation confirmation, especially in contexts where user expectations are rapidly evolving?*** This question underscores the need for a deeper examination of the factors influencing both adoption and long-term engagement with AI-based mobile applications.

Literature Review

1. An Enriched ECM: Extending the Model with Personalization

The Expectation–Confirmation Model (ECM), developed by Bhattacherjee (2001), was inspired by two pre-existing frameworks, namely Expectation–Confirmation Theory (ECT) and the Technology Acceptance Model (TAM) (Jumaan, 2020). Originally formulated by Oliver (1980), ECT seeks to explain the variables influencing post-purchase behavioral evaluations. The model unfolds as follows: first, consumers form initial expectations regarding a product or service prior to purchase (t1). Second, they adopt and use the product or service, thereby forming perceptions of its performance after an initial consumption phase (t2). Third, consumers assess the perceived performance relative to their initial expectations, thereby determining the degree of confirmation. Fourth, satisfaction or dissatisfaction arises depending on the level of confirmation. Finally, satisfied consumers are likely to repurchase the product or service, whereas dissatisfied users tend to discontinue usage.

Drawing on this logic, Bhattacherjee (2001) extended ECT to propose ECM as a framework for explaining continuous usage intention of information systems. According to Bhattacherjee, a user's decision to continue using an information system parallels a consumer's decision to repurchase a product or service. However, he also argued that ECT does not sufficiently account for potential changes in expectations after actual use, nor for the impact of these changes on subsequent cognitive processes. Expectations often evolve with experience, meaning that post-adoption expectations may differ from pre-adoption ones. Pre-purchase expectations are typically shaped by external information, such as word-of-mouth or media, whereas post-acceptance expectations are moderated by direct user experience, rendering them more realistic (Fazio & Zanna, 1981).

To address this limitation, Bhattacherjee (2001) replaced the construct of “expectation” with “perceived usefulness.” Within this revised model, both perceived usefulness and confirmation influence satisfaction, which in turn shapes continuous usage intention. Perceived usefulness also exerts a direct effect on continuous usage intention, while confirmation positively affects perceived usefulness. Empirical results indicate that satisfaction is the most critical predictor of continuous usage intention, closely followed by perceived usefulness.

The ECM thus emerges as one of the earliest frameworks to integrate major constructs perceived usefulness, expectation confirmation, and satisfaction into the explanation of continued information system use (Meidani et al., 2022). Its enduring relevance lies in its ability to capture the cognitive mechanisms underlying long-term engagement with digital technologies.

2. Hypotheses and Research Model

2.1 The Effect of Satisfaction on the Intention to Continue Using AI-Based Applications

In marketing literature, satisfaction is widely recognized as a critical determinant of customer loyalty, serving as a cornerstone for establishing and sustaining long-term consumer relationships. Anderson and Sullivan (1993) metaphorically describe customer satisfaction as “an insurance policy,” underscoring its strategic importance for firms. A similar dynamic has been anticipated in the field of information systems, where user satisfaction with a system consistently strengthens the intention to continue its use (Bhattacherjee, 2001; Jumaan, 2020).

Satisfaction has been conceptualized in multiple ways. Cadotte et al. (1987) define it as “a feeling resulting from the evaluation of the usage experience,” while Halstead et al. (1994) describe it as “a specific affective response to a transaction, arising from the consumer’s comparison of product performance to a prior purchase standard.” Bhattacherjee (2001) frames satisfaction as “a psychological or affective state associated with a cognitive evaluation of the gap between expectations and performance.” In the context of AI-enabled mobile applications, satisfaction can thus be understood as an emergent affective response derived from evaluating one’s lived experience with such applications.

Empirical studies across diverse contexts have consistently validated the satisfaction–continuance link. In educational settings, Liao et al. (2009), Joo et al. (2018), and Huang (2019) demonstrated the positive influence of satisfaction on students' intention to adopt emerging technologies. Within internet-related research, Lin et al. (2005) and Hsu et al. (2014) found that satisfaction favorably impacts users' intentions to continue web browsing and to engage with social networking platforms. Parallel findings have emerged in the context of mobile applications, where multiple studies confirm the positive correlation between satisfaction and continuance intention (Xu et al., 2015; Cho, 2015; Yuan et al., 2015; Li & Fang, 2019; Alshurideh et al., 2020; Jumaan, 2020; Gupta et al., 2020). This relationship has also been substantiated in the domain of artificial intelligence applications (Ashfaq et al., 2020; Kashive & Powale, 2020; Nguyen et al., 2021).

H1. User satisfaction with the AI-based application positively influences the intention to continue its use.

2.2. The effect of perceived usefulness on satisfaction and the Intention to Continue Using AI-Based Applications

The integration of new technologies into everyday life depends not only on their technical sophistication but on the meanings individuals attribute to them. Central to this process is the notion of perceived usefulness, defined as the belief that a system enhances the accomplishment of one's goals or tasks (Bruner & Kumar, 2003). While the literature in marketing and information systems has long established perceived usefulness as a driver of adoption, its significance transcends the instrumental. It embodies a normative judgment regarding whether a technological artifact deserves a place in the rhythms of daily life.

In the context of AI-based applications, usefulness is often equated with efficiency, personalization, and immediacy. Users embrace applications that eliminate friction such as repeated website visits while providing access to what they desire in more tailored ways. Yet, usefulness is not a neutral construct; it rests on a practical philosophy of technology in which utility shapes, and is shaped by, expectations of human machine interaction. The utilitarian logic of "usefulness" has thus become a cultural imperative: an application that fails to be useful is not merely ignored, it is deemed irrelevant.

Empirical studies have consistently shown that perceptions of usefulness positively correlate with user satisfaction and the intention to continue use. However, the deeper question concerns why usefulness exerts such influence. One explanation is phenomenological: when users perceive AI systems as genuinely supportive of their practical endeavors whether searching for information, making purchasing decisions, or navigating complex choices they experience a form of technological alignment that strengthens satisfaction. Another explanation is teleological: continued use presupposes that a technology not only functions but justifies its presence by contributing to a perceived “good.” In this sense, satisfaction is not merely hedonic but existential, affirming that the technology is worth integrating into one’s life-world.

Thus, perceived usefulness functions as a hinge between technological rationality and human flourishing. Where users discern tangible benefits, satisfaction arises, and continuance intention follows as a rational extension of this satisfaction. Conversely, if usefulness is absent, neither satisfaction nor sustained use can be expected. From this perspective, we propose the following hypotheses:

H2. Perceived usefulness of the AI-based application has a positive effect on user satisfaction.
H3. Perceived usefulness of the AI-based application has a positive effect on users’ continuance intention.

2.3. The impact of expectation confirmation regarding the AI-based application on perceived usefulness and continuance intention

Within the framework of the Expectation–Confirmation Model (ECM), users who initially engage with a novel technology often do so with only partial knowledge of its actual performance. Their adoption intentions, therefore, are largely grounded in anticipatory beliefs rather than in direct experience. Once the technology is employed, these expectations are either confirmed or disconfirmed, thereby reshaping both the perceived usefulness of the system and the degree of satisfaction it affords.

For instance, users may initially approach an “intelligent” application with modest or even skeptical expectations, uncertain about what such technology can truly deliver. In such cases, their adoption decision is less a rational calculation and more a projection a willingness to engage with the technology in the hope that subsequent experience will clarify its value. Positive confirmation can then recalibrate these initial doubts, leading to a recognition that the technology is not only functional but exceeds what was originally imagined.

This dialectic between expectation and lived experience has been consistently documented across research on emerging technologies (Thong et al., 2006; Nascimento et al., 2018), the internet (Liao et al., 2005; Lin et al., 2005; Veeramootoo et al., 2018), mobile marketing (Hsiao & Chang, 2013; Yuan et al., 2014), mobile applications (Cho, 2016), and, more recently, artificial intelligence (Nguyen et al., 2021; Alnaser et al., 2023).

Expectation confirmation thus functions not merely as a cognitive adjustment but as a phenomenological process in which human anticipation is confronted with technological reality. When the confrontation is positive, users not only revise their assessment of usefulness but also reaffirm the legitimacy of continuing their engagement with the system. Accordingly, we propose the following hypotheses:

H4. Confirmation of expectations regarding the AI-based application positively influences users' perceived usefulness.

H5. Confirmation of expectations regarding the AI-based application positively influences users' continuance intention.

2.4. The Effect of Personalization on the Intention to Continue Using AI-Based Applications

Beyond the relations postulated by the Expectation–Confirmation Model, one feature intrinsic to artificial intelligence demands particular attention: personalization (Zanker et al., 2019). Within the paradigm of *"Thinking AI"* that is, systems designed to analyze data in order to generate new conclusions or decisions (Huang & Rust, 2020) personalization emerges as both a technical capability and a philosophical promise. Through mechanisms such as facial recognition, voice recognition, or textual analysis, AI systems tailor information and recommendations to individual users, producing the impression that the technology "knows" them.

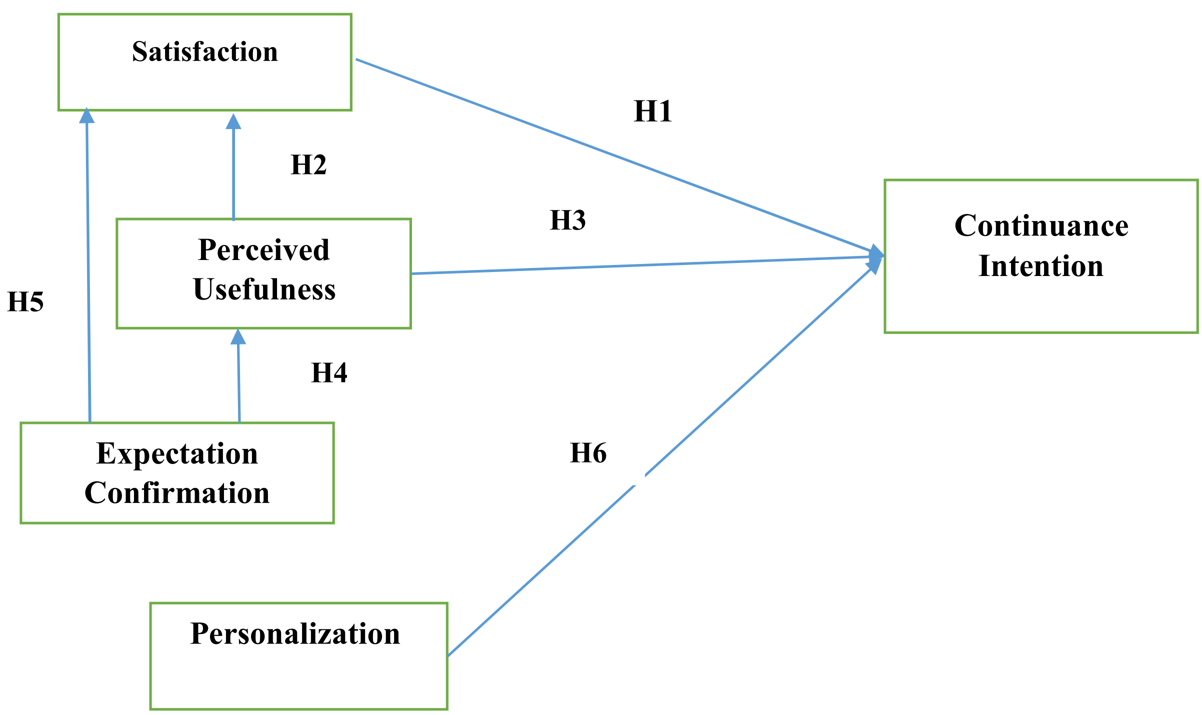
Personalization has been celebrated as a decisive factor in the success of AI (Kumar et al., 2019), for it allows individuals to navigate vast information environments with unprecedented efficiency. By filtering content to match a user's specific needs and preferences, personalization positions itself as a guarantor of relevance and immediacy. As Ameen et al. (2021) observe, personalization may be defined as "the extent to which information is tailored to the needs of a unique user, thereby constituting a key determinant of positive experiences."

Empirical studies across domains from health applications (Guo et al., 2016) to hospitality apps (Cristian & DeFranco, 2016) and e-commerce platforms (Song et al., 2021) corroborate the claim that personalization significantly enhances behavioral intentions. In the sphere of artificial intelligence specifically, personalization has been shown to positively shape both user trust and continuance intention (Pillai et al., 2020; Yoon & Lee, 2021).

Yet personalization is not merely a functional advantage; it carries a deeper normative implication. To the extent that a system adapts itself to the contours of an individual's life-world, it asserts a claim to indispensability. Users perceive the technology not simply as a tool but as an interlocutor that anticipates their needs, thereby reinforcing the legitimacy of continued engagement. In this sense, personalization is not only an attribute of design but also a condition of technological attachment. Accordingly, we propose the following hypothesis:

H6. Personalization of the AI-based application positively influences users' continuance intention.

Figure 1: Conceptual Model



3. Methodology

To ensure the relevance and robustness of the findings, this study was conducted through an online survey of 300 participants, aged between 16 and over 60 years. In order to validate that each respondent had indeed interacted with an AI-based application, a screening filter was introduced at the beginning of the questionnaire, requiring participants to specify the applications they had previously used (e.g., Airbnb, Booking.com). This precaution safeguarded the relevance of the responses and enhanced the reliability of the dataset.

The constructs examined in this study perceived usefulness, expectation confirmation, personalization, satisfaction, and continuance intention were measured using established scales drawn from prior literature. These instruments have been shown to demonstrate reliability and validity across different technological contexts. For scales originally available only in English, we followed the standard double back-translation procedure to ensure linguistic and conceptual equivalence. Furthermore, the vocabulary was carefully adapted to the specific context of AI applications, thereby securing stronger content validity.

Table 1. Summary of the Measurement Scales for the Study Variables

Variables	Author(s)	Number of Items
Perceived Usefulness	Davis et al. (1989)	4
Expectation Confirmation	Bhattacherjee (2001)	3
Satisfaction	Bhattacherjee (2001)	4
Personalization	Xu (2011)	3
Continuance Intention	Bhattacherjee (2001)	3

4. Results

4.1. Exploratory and Confirmatory Analyses

To examine the psychometric properties of the measurement instruments, both exploratory and confirmatory factor analyses were conducted on a sample of 300 participants using SPSS 20 and Smart PLS 4. The exploratory analysis indicates that the dataset is amenable to factorization, as all Kaiser–Meyer–Olkin (KMO) values exceeded 0.5 and Bartlett's test of sphericity was significant at the 5% threshold. These findings suggest that the underlying constructs are adequately represented and suitable for factor analysis.

Reliability was assessed via Cronbach's alpha, with all scales surpassing the 0.7 benchmark, thereby demonstrating satisfactory internal consistency (Nunnally, 1978). In evaluating the quality of representation, items with factor loadings below 0.5 or cross-loading significantly on multiple factors were slated for removal due to their limited discriminatory power. In this study, all items met these criteria, ensuring a robust measurement structure.

The determination of the number of factors to retain was guided by the Kaiser criterion, considering factors with eigenvalues greater than 1. Notably, all measurement scales proved unidimensional, confirming that each set of items coherently captures a single conceptual construct.

From a philosophical perspective, these results not only establish the empirical adequacy of the instruments but also reflect the *conceptual integrity* of the constructs under investigation. That is, the unidimensionality of the scales underscores the coherence between the theoretical definitions of constructs such as perceived usefulness, expectation confirmation, personalization, satisfaction, and continuance intention, and their operational manifestations in empirical measurement.

Table 2: Exploratory and Confirmatory Analyses

Variables	Bartlett's Test of Sphericity	KMO	Sig de Bartlett	Cronbach's Alpha
Continuance Intention	2.466	0.741	0.000	0.890
Perceived Usefulness	3.404	0.856	0.000	0.938
Satisfaction	3.369	0.785	0.000	0.937
Expectation Confirmation	2.245	0.606	0.000	0.824
Personalization	2.653	0.756	0.000	0.935

The results of the confirmatory analysis indicate that all constructs exhibit satisfactory composite reliability, with values exceeding the conventional threshold of 0.7, and that all items load strongly on their respective constructs, with factor loadings above 0.7 (Hair et al., 2009). This empirical coherence not only ensures statistical reliability but also reflects the conceptual fidelity of the constructs: each set of items effectively operationalizes the theoretical notion it intends to capture.

Convergent validity was further assessed through the examination of Average Variance Extracted (AVE), all of which surpassed the acceptable threshold of 0.5 (Chin, 1998). Discriminant validity was confirmed by verifying that the square root of the AVE for each construct exceeded the shared variance with other latent variables, thus establishing the distinctiveness of each conceptual domain (Fornell & Larcker, 1981).

Prior to testing the proposed hypotheses, it is essential to evaluate the predictive adequacy of the structural model. This involves assessing the explanatory power of the latent constructs via the coefficient of determination (R^2) (Fernandes, 2012). Following Cohen's (1988) guidelines, as cited in Wetzel et al. (2009), R^2 values of 0.02, 0.13, and 0.26 are conventionally interpreted as indicating small, medium, and large explanatory effects, respectively. In the present study, PLS-based analyses reveal R^2 values that attest to satisfactory predictive relevance for all dependent variables.

From a conceptual standpoint, these results provide more than mere statistical validation: they substantiate the structural coherence of the theoretical model. The robust reliability, convergent, and discriminant validity of the constructs imply that the latent variables perceived usefulness, expectation confirmation, personalization, satisfaction, and continuance intention form an internally consistent and distinct system, thereby reinforcing the interpretive legitimacy of the subsequent hypothesis testing.

Table 3: Summary of the Measurement Model Evaluation

Variables	Cronbach's Alpha	CR	AVE	R^2
Continuance Intention	0.892	0.893	0.822	0.850
Perceived Usefulness	0.942	0.942	0.851	0.706
Satisfaction	0.936	0.938	0.842	0.800
Expectation Confirmation	0.823	0.915	0.746	
Application Personalization	0.935	0.939	0.884	

4.2. Structural Model Results

To examine the direct relationships among the constructs under investigation, the Partial Least Squares (PLS) approach was employed. The results, summarized in the table below, indicate that all hypotheses derived from the proposed conceptual model are supported.

Beyond the mere statistical confirmation, these findings carry conceptual significance. The empirical validation of the model suggests that the theorized relationships linking perceived usefulness, expectation confirmation, personalization, satisfaction, and continuance intention reflect coherent and intelligible patterns of human interaction with AI-based applications. In other words, the structural model does not simply quantify relationships; it affirms the conceptual plausibility that the operationalized constructs indeed capture meaningful dimensions of technological engagement and human judgment.

Table 4: Empirical Testing of Direct Relationships in the Conceptual Framework

Hypothesis	β (Path Coefficients)	Student's t-test	P-values
H1. User satisfaction with the AI-based application positively influences the intention to continue its use.	0.240	4.558	0.000
H2. Perceived usefulness of the AI-based application has a positive effect on user satisfaction.	0.253	4.283	0.000
H3. Perceived usefulness of the AI-based application has a positive effect on users' continuance intention.	0.559	9.614	0.000
H4. Confirmation of expectations regarding the AI-based application positively influences users' perceived usefulness.	0.840	44.277	0.000
H5. Confirmation of expectations regarding the AI-based application positively influences users' continuance intention.	0.671	12.195	0.000
H6. Personalization of the AI-based application positively influences users' continuance intention.	0.162	2.635	0.008

5. Discussion of Results

The findings of this study substantiate the relevance and robustness of the enriched Technology Acceptance Model (TAM), demonstrating that multiple factors significantly shape users' intentions to continue engaging with an ECM-based system. The empirical validation of all hypothesized relationships confirms both the theoretical coherence of the model and its capacity to illuminate patterns of technology adoption within organizational contexts.

A central observation concerns the positive and significant relationship between user satisfaction and continuance intention. Consistent with prior research (Alshurideh et al., 2020; Jumaan, 2020; Gupta et al., 2020), these results suggest that satisfaction operates not merely as a transient affective response but as a driver of durable integration of technology into daily practices. Satisfaction thus functions as a lever for sustained engagement, extending beyond the initial phase of adoption.

Perceived usefulness emerges as another critical determinant, aligning with the foundational insights of Davis (1989). It influences not only the intention to adopt technology but also satisfaction and the willingness to maintain its use over time. When a system is judged effective in accomplishing intended tasks, it generates tangible value, which in turn enhances user satisfaction (Alshurideh et al., 2020; Yan et al., 2021). Satisfaction then becomes a mechanism through which long-term commitment is fostered, illustrating the dual role of perceived usefulness as both a cognitive precursor and a driver of loyalty (Venkatesh & Davis, 2000).

Expectation confirmation similarly plays a pivotal role by influencing both perceived usefulness and satisfaction. When user experiences meet or exceed initial expectations, the system is recognized as more useful because it concretely fulfills operational needs. This confirmation generates positive evaluations of the user experience, reinforcing satisfaction. These findings resonate with Bhattacherjee's (2001) ECM framework, which conceptualizes confirmation as a central lever affecting both cognitive judgments (usefulness) and affective attitudes (satisfaction).

Personalization constitutes a further determinant of continuance intention. By tailoring information or services to individual needs, AI-based applications enhance the overall user experience and satisfaction. Prior research across domains including e-commerce, mobile health applications, and AI-based systems confirms that perceived personalization positively shapes behavioral intentions (Guo et al., 2016; Song et al., 2021; Pillai et al., 2020; Yoon &

Lee, 2021). High levels of personalization thus encourage continued engagement, transforming superficial adoption into meaningful, sustained interaction.

From a theoretical standpoint, this study extends the ECM by integrating personalization as a key determinant of continuance intention, particularly in the context of AI applications. Leveraging *Thinking AI*, which analyzes data to generate personalized decisions, the study highlights the interplay of satisfaction, perceived usefulness, expectation confirmation, and personalization in shaping technological engagement. Personalization emerges not merely as a functional feature but as a mediator of meaningful interaction, amplifying the alignment between system capabilities and individual user needs.

Practically, the findings offer actionable insights for developers and organizations seeking to maximize adoption and retention in the rapidly evolving AI landscape. Emphasizing personalization enables designers to create interfaces and functionalities that dynamically respond to user preferences and requirements. By moving beyond superficial adaptation, AI can facilitate immersive, individualized experiences that anticipate user needs, save time, and deliver tangible value.

Ultimately, this approach centered on personalization and attentive to satisfaction, perceived usefulness, and expectation confirmation transforms initial usage intentions into durable commitment. In highly competitive digital environments, such a strategy not only enhances brand differentiation and corporate reputation but also generates a virtuous cycle of engagement and long-term value creation.

Conclusion

This study, grounded in the Expectation–Confirmation Model (ECM) enriched by personalization, provides a nuanced understanding of the factors influencing continuance intention in technology adoption, particularly within the realm of artificial intelligence (AI). Drawing upon Bhattacherjee’s (2001) ECM framework which emphasizes the pivotal roles of satisfaction, perceived usefulness, and expectation confirmation our research highlights personalization as a critical determinant of user experience and long-term engagement.

By tailoring information and services to the specific needs of individual users, AI-based applications can cultivate stronger engagement and higher satisfaction, thereby fostering sustained intention to continue usage. Rigorous statistical analyses conducted on a sample of

300 participants using SPSS 20 and Smart PLS 4 confirm the reliability and conceptual adequacy of the proposed model, demonstrating robust internal consistency as well as convergent and discriminant validity. These findings offer both theoretical and practical insights for scholars and practitioners seeking to optimize long-term adoption of AI applications, underscoring personalization as a key lever for enhancing user engagement.

From a conceptual perspective, personalization transcends its operational function; it mediates a meaningful interaction between technology and user, aligning system capabilities with individual needs and expectations. By integrating this dimension, developers and organizations can not only improve user experience but also cultivate durable engagement and loyalty in rapidly evolving technological environments.

Several avenues for future research emerge from this study. First, it would be fruitful to examine the moderating effects of contextual variables such as organizational culture or industry sector on the relationships between personalization, satisfaction, and continuance intention. Second, a longitudinal approach could shed light on how these relationships evolve over time, accounting for user learning and adaptation processes. Third, further research could investigate specific dimensions of personalization (e.g., content, interface, or recommendation customization) to determine which aspects most strongly drive continuance intention. Finally, qualitative studies could complement quantitative findings by capturing richer insights into user experiences and perceptions regarding AI personalization.

In sum, this study advances the theoretical understanding of ECM in AI contexts, emphasizing personalization as a conceptual and practical linchpin in fostering sustained technological engagement. It illustrates that enduring adoption is not merely a function of system functionality, but also of the capacity of technology to resonate with and respond meaningfully to individual users' expectations and needs.

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Appendix

Structural Model Estimation Using Smart PLS 4

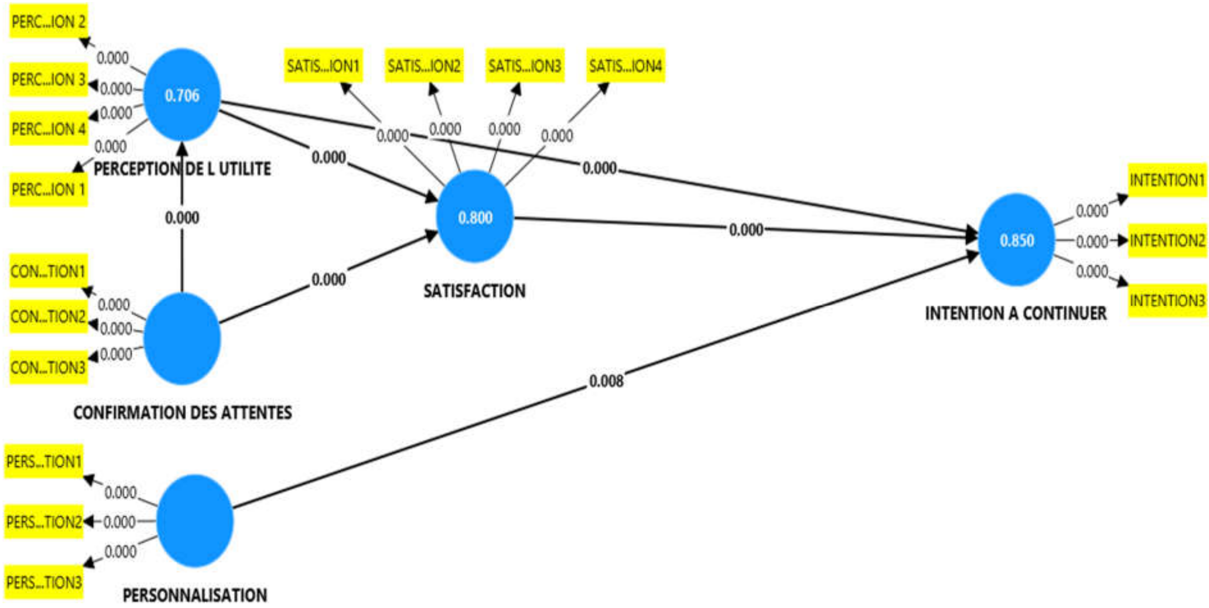

Table 4: Sample Sociodemographic and Professional Characteristics

	Variables	pourcentage
Gender	Male	36%
	Female	64%
Age	18--- 29 yrs	20%
	30--- 45 yrs	36%
	46---59 yrs	30%
	60 and above	14%
Occupation	Student	16%
	Employees	34%
	Retirees	12%
	Others (merchants, business owners, craftsmen, etc.)	38%