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Artificial Intelligence-Powered Customer Experience and Consumer Retention: The Role of Personalization

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Abstract

While the widespread integration of Artificial Intelligence into the world of Customer Experience Management has opened up new possibilities for personalising the experience on a scale never before seen, the ways in which such experiences can impact customer retention through personalisation have yet to be thoroughly explored—especially when it comes to new market contexts. The study was conducted using an AI-Powered Customer Experience (AIPCE) for online retail, streaming platforms, and banking apps, as well as customer personalization (CP) in the service area, within the context of the Personalization Theory and the Customer Relationship Management (CRM) Theory, and tried to determine the influence of AI-Powered Customer Experience (AIPCE) on the relationship between Customer personalization (CP) and Consumer Retention (CR). A quantitative causal research design was used and primary data gathered with a stratified sampling technique, ensuring proportional sampling across three sectors, 250 respondents. An instrument based on a structured questionnaire, with validated scales was used which included AIPCE (20 items), Personalization (14 items) and CR (10 items). The data was analyzed by SPSS and AMOS software version 28.0 and 26.0 respectively. Demographic analysis, descriptive statistics, reliability and validity testing, CFA and SEM were performed. The model was found to be satisfactory for being fit (CFI = 0.954, TLI = 0.947, RMSEA = 0.051, SRMR = 0.048) and was sufficiently valid for constructs (Tot = Good (CFI > 0.900 and TLI > 0.900, RMSEA < 0.050 and SRMR < 0.050)). SEM results demonstrated significant direct effects of AIPCE on Personalization (beta = 0.641, p < 0.001) and CR (beta = 0.298, p < 0.001), and of Personalization on CR (beta = 0.421, p < 0.001). There was partial mediation in the relationship between AIPCE and CR with the mediation model obtaining for personalization (indirect effect = 0.270, 95% CI: 0.189-0.351, p < 0.001) with 47.5% of the total effect. The model accounted for 62.3% of the variance in Consumer Retention. The AIPCE-CR direct relation was stronger in the banking sector, and the perceptions of the Personalization were higher among the users of streaming platforms. Findings contribute to the Personalization Theory for AI-service environments, and provide realistic insights to guide the CRM strategies in digitally-oriented service industries.

Introduction

Artificial Intelligence technology has changed the way that Customer Experience Management is thought of: shifting from mass market and segment level to truly unique customer engagements at a population scale. Using machine learning algorithms that draw on massive amounts of behavioural and transactional data, as well as contextual data, is now making it possible to achieve some of the personalisation benefits that could only be accomplished in a high-touch version of the service before – through user service relationships and human servicepersons.Combining large amounts of behavioural, transactional, and contextual data allows AI-powered personalisation systems to leverage machine learning algorithms and dynamically recommend products, adjust content, predict service relevant actions, and even communicate with services to the individual user, reproducing some of the personalisation effects traditionally attributed to personal service relationships and high-touch human service. There is a clear recurring theme within the business usage discourse about the benefits that personalisation at a large scale can bring to a business volume wise: McKinsey (2021) concluded that the organisations that are most successful with personalisation at a large scale can expect to experience 10-15% revenue uplift, whereas Epsilon (2017) identified that 80% of consumers are more likely to purchase from brands that provide personalised experiences.

While the body of academic work on AI and customer experience (CX) has increased rapidly, its application to understanding how improved customer experience through AI impacts customers' retention has not been fully explored—with personalisation as a mediator in this relationship remaining largely under-revestigated. The service marketing literature has long theorised that personalisation – which entails product, service, communications and interactions (PSCI) catering to the personal characteristics, preferences and behavioural history of specific customers – can be a key determinant of customer satisfaction and loyalty (Peppers & Rogers, 1997). Theoretically, algorithmic personalisation can be based on extensive customer data profiles, continually refined through machine learning, and can offer the same or better retention results than human personalisation, rendering the question of whether algorithmic or human services offer the same or more retention results an interesting one to explore.

Based on the findings from previous research, one of the main aims of CRM strategy is to encourage consumer retention, which is demonstrated from customers' willingness and tendency to keep purchasing a firm's products and services over time, illustrated by repeat purchase behaviour, brand loyalty feelings and positive advocacy for the firm through word-of-mouth (Reichheld, 1996; Payne & Frow, 2005). Theory on the retention value of personalisation through AI builds on CRM theory, by offering theoretical support in understanding how AI personalisation helps organisations achieve the retention strategy that CRM theory prescribes (individual level relationship management for the creation of long-term value). AI-driven systems can provide better and faster service to each customer by identifying and responding quickly and correctly and without variation to their individual needs, tastes and behavior when compared with human service agents, thus improving the relational nature of the interactions that happens between them and the organisation, increasing the commitment and switching costs that in turn would contribute to long-term customer retention.

The three sectors chosen for this study - online sales, streaming applications, and banking and finance - are where AI-powered personalisation has been most widely implemented and could have the greatest impact on consumer behaviour, and thus business success. In the electronic commerce (e-commerce) industry, product recommendation systems, which are based on the collaborative filtering principle and deep learning, are the common platform architecture solution for product discovery; a reported 35% of Amazon purchases are made using their recommendation systems (Linden et al., 2003). In streaming, the recommendation system built by the Netflix artificial intelligence is said to save the company by about USD $1 billion annually due to fewer churns, with about 75-80% of the company's viewing hours attributable to its AI-powered recommendations (Gomez-Uribe & Hunt, 2016). In the banking industry, artificial intelligence customization can lead to proactive financial counseling, personalized product recommendations, and predictive fraud detection, thereby boosting customer-bank interactions, both in terms of services and financing (Ngai et al., 2009). Although a number of sectors are undergoing the implementation of AI personalisation, the existing academic literature is lacking in comparative evidence based on a unified theoretical framework to explain the way AI personalisation is implemented in each sector, specifically through the AIPCE-Personalization-CR pathway.

Based on the one-to-one marketing concept conceptualised by Peppers and Rogers (1997) with later empirical research on the psychological and behavioural responses of personalised service interactions, the Personalization Theory posits that in customers, the perceived personalisation will trigger positive affective and evaluative responses such as feeling valued, understood, and uniquely catered for, resulting in increased satisfaction and loyalty (Arora et al., 2008). The construct of perceived personalisation must be differentiated from the algorithmic personalisation process, as the key for customers' behaviours outcomes is the generational relevance, timeliness and personalisation of the experience achieved by the algorithm, rather than the complexity of the algorithmmatic process (Tam & Ho, 2006). This perceptual aspect of personalisation is even more psychological, in that it demands measuring customer perceptions from a survey exercise, not only algorithmic parameters, in the context of artificial intelligence.

The present study adds to the literature by firstly applying an empirical test of the Personalization-mediated pathway from AI-powered Customer Experience to Consumer Retention with a covariance-based SEM approach (AMOS) that allows a proper analysis of the quality of the measurement model simultaneously to the structural model. The cross-sector stratified design allows for testing the overall model, and for conducting a sector-comparative analysis on whether the AIPCE-Personalization-CR pathway is applied in a similar manner in retail, streaming and banking scenarios, which has immediate implications for sector specific AI personalisation strategy.

Literature Review

Considering literature on the theoretical bases of this study reinforces a need to examine the cross-over literature on AI in marketing, service personalisation, customer experience management and consumer retention. These streams have evolved concurrently, and becoming more and more intertwined as AI is the main lever that makes personalisation and experience management a reality in digital environments. Theoretically sound, and empirical linking of these streams are key to the modelling of AIPCE-PR relationship in a theoretically coherent and empirically valid way.

The scope of a customer experience with AI (CXAI) includes all interactions that are shaped by AI along the customer journey, ranging from recommendation interactions to interactions with conversational AI, to interactions with predictive services, to the dynamically personalised content encounters (Lemon & Verhoef, 2016). Various AI characteristics have been identified as dimensions of the quality of AI-powered experience, including the perceived intelligence/competence of AI recommendations, their perceived relevance and timeliness, the seamless experience of using AI to assist humans, AI interaction tone and responsiveness, and the trustworthiness of AI system intentions and capacities (Huang & Rust, 2021). These dimensions overlap with conventional models of service quality, but need to be extended to account for the particular qualities of AI service agents, such as their scale, uniformity, data loading, and impact on consumer psychology in interacting with a non-human intelligence (Mende et al., 2019).

The use of personalisation in service context has been theorised to work in two main ways: firstly, by enhancing the relevance of the services and products the customer receives, thereby lowering the costs of handling information and increasing the usefulness/value of the information for the individual customer (relevance-enhancement); and secondly, by signaling to the customers that the service provider has spent attention and resources to understand their needs until they reach the point of an expected service (relational-signalling) (Arora et al., 2008, Tam & Ho, 2006). Both mechanisms are mediated by the personalisation system that uses Artificial Intelligence technology, which might be more effective than the human personalisation system because it can process and react to much more data regarding customers' behaviour (Tran et al., 2021). In the context of searching for personalisation, a theoretic and practical problem of whether AI-mediated personalisation produces equivalent relational responses to human-mediated personalisation is addressed, only partly, in the present investigation, which focuses on the personalisation-retention pathway in the AI service context.

AI personalisation functions as a retainment tool within a strategic and organizational framework outlined by Customer Relationship Management (CRM) theory. Payne and Frow (2005) CRM framework recognized as the key “processes” areas in an effective CRM: value creation, integration of multiple channels, information management and performance assessment where personalisation is seen as the key process of value creation, in which individual customer relationships are developed and maintained. AI technologies enhance all four parts of the CRM process—machine learning creates individual value through precision personalisation, digital channels systems can be integrated for seamless cross-channel AI personalisation, big data systems can now make information management possible for individualised CRM, and customer lifetime value modelling can predict user value based on customer usage, allowing anticipated results for retention investments to be assessed more accurately (Ngai et al., 2009). The qualitative leap represented by the implementation of the AI-based advanced CRM function is to move from an aspirational one-to-one marketing, which - due to limited human cognitive and information processing power - is only possible on a small-scale level, to mass-implementation of the “personalisation at the individual level” principle.

Since around 2015, considerable empirical data about AI personalisation and consumer outcomes have been gathered. The link between AI personalisation to retention within the sector has been best documented in Netflix by Gomez-Uribe and Hunt 2016, documenting the streaming sector's proven retention effects from recommendations. For eCommerce, Zhang et al. (2019) found that the relevance of a recommendation, as determined by AI, is a strong factor in predicting purchase intention and repeat visit intention, and that the perceived personalisation of the recommendation fullymediated the relationship between AI recommendation quality and both purchase intention and repeat visit intention. For the banking sector, Tan et al. (2021) discovered that personalised financial insights enabled by AI have a significant positive effect on customer engagement and adoption of products, and customers' perception of personalisation is an intervening condition between AI capability and intention to retain the bank. However, these studies focus on specific sectors do not allow for cross-sector comparisons, have not been simultaneous trials of the whole AIPCE-Personalization-CR mediation pathway based on CFA valid constructs and are mostly conducted in familiar setting of the US and Europe which may have significantly different maturity of AI deployment and AI consumer experience than that of emerging market countries like Pakistan.

The multi-sector approach to the current study is driven by the level of customer experience and perceived value that exists between sectors for personalisation using AI. The customers of streaming services experience AI personalisation mainly when content is being discovered – the better the recommendations the more valuable the service offering, and a service failing at this crucial point has an immediate and stark impact on the customer in the form of suggestions for content they're not interested in. Retail customers experience AI personalisation in the form of product suggestions, promotions, and even the ranking of search results, which improve purchase efficiency, yet are just one of several factors that help determine purchase. In banking, for instance, AI-driven personalisation influences retention through proactive financial guidance, product suggestions, and security warnings, potentially shaping the relationship between personalisation and retention in distinct ways compared, say, to retail or streaming scenarios, notably where issues of quality and control, customer trust, and regulatory compliance might play different roles in how the two are linked (Wedel & Kannan, 2016). Testing the mediation model in the three contexts within a single study allows for a general test of the theoretical model as well as for insights that are specific to each context and cannot be obtained from previous studies conducted in single contexts.

The literature summary shows that there is a solid theoretical infrastructure that supports the proposed AIPCE-Personalization-CR mediation model developed based on Personalization Theory and CRM Theory, along with a set of increasing but disjointed empirical results to support the model relationships in specific sector contexts. The present integrated and cross-sector, CFA-validated mediation study is a substantive step in theoretical integration and empirical scope, and findings are expected to have theoretical and practical implications for the managers of services using AI personalisation in the three key sectors identified.

Methodology

Research Design

A quantitative causal research design was employed and this was proper for the testing of the hypothesised direction of relationships between AIPCE, Personalization, and CR. With a cross sectional survey design, a large (stratified) sample could be studied within a limited period of time, and covariance-based SEM (CB-SEM) allowed for the quality of the measurement model and the structural relationships to be tested simultaneously in a rigorous way, using AMOS. Informed electronic consent was secured via approval from the Institutional Research Ethics Committee and all respondents gave electronic consent prior to accessing the survey.

Population, Stratified Sampling, and Data Collection

The sample consisted of adult consumers that used AI capabilities in online retailing, streaming platforms or any banking application within the past three months, such as obtaining personalised suggestions for offers, predictions based on content or interactive finance tips. Stratified sampling was used to obtain the desired allocation of approximately 84 per sector (total n = 250). To operationalise the concept of sector strata, the participants were screened for the major context in which they use AI services. An online survey was conducted using Google Forms which was sent to Kenses in the professional networks, alumni of universities and user community of the respective sectors within Lahore, Karachi and Islamabad. Of the 286 surveys received, 36 did not contain the full necessary information, or had people who failed to meet the survey requirements (non-users in target sectors), leaving an analytical sample of 250 (84 retailing, 88 streaming, 78 banking).

Measurement Instrument

There were four sections to the structured questionnaire. Information on demographics and use across sectors was gathered in Section 1. For AI-Powered Customer Experience, 20 items were selected to measure the four dimensions of AI competence, interaction quality, seamlessness, and emotional experience, as adapted from Lemon and Verhoef (2016), Huang and Rust (2021), and Flavian et al. (2022). For the Personalization construct measured in section 3, 14 items were adapted from Tam and Ho (2006) and Arora et al. (2008), and measured the aspects of relevance, timeliness, individualisation and relational signalling. Consumer Retention was assessed in terms of 10 items that borrow from the scales developed by Reichheld (1996) and Payne and Frow (2005) and indicators of repurchase intention, attitude towards loyalty, advocacy behaviour. On all items, responses were based on a five point Likert-type response scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Urdu translation and back-translation of this instrument were performed, and a few words were changed based on the cognitive interviews held with five bilingual respondents.

Confirmatory Factor Analysis and SEM

To evaluate the measurement model validity before testing the measurement model, CFA was undertaken using AMOS 26.0 with maximum likelihood estimation. Several model fit indices including the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) were obtained and compared to standard cut-off scores (CFI and TLI > 0.90) and the Root Mean Square Error of Approximation (RMSEA) and the Standardised Root Mean Square Residual (SRMR) with cut-off scores of < 0.08. The reliability test used was Cronbach alpha and components reliability, convergent validity test was AVE and standardised factor loading, and discriminant validity was Fornell-Larcker criterion and HTMT ratio. Full information maximum likelihood

(FIML) SEM with mediation analysis carried out via bootstrapping with 5,000 samples and bias-corrected 95% confidence intervals (CIs) were used for testing the structural model.

Analysis and Results

Primary Demographic Profile of Respondents

The 250 respondents were given a demography and sector base distribution as shown in table 1.

Variable	Category	n	%
Gender	Male	144	57.6%
	Female	106	42.4%
Age	18-24	62	24.8%
	25-34	108	43.2%
	35-44	56	22.4%
	45+	24	9.6%
Education	Undergraduate	74	29.6%
	Postgraduate	124	49.6%
	Professional/Other	52	20.8%
Primary Sector	Online Retailing	84	33.6%
	Streaming Platforms	88	35.2%
	Banking Applications	78	31.2%
AI Usage Frequency	Daily	102	40.8%
	Several times/week	96	38.4%
	Weekly or less	52	20.8%

Table 1. Demographic profile of respondents (n=250)

The sample had good sectoral stratification with close to the target representation less than 35% representing sectors such as retail (33.6%), streaming (35.2%) and banking (31.2%). The majority of people (43.2 %) are within the age group of 25–34 and more than half (49.6%) have completed higher education, which indicates Pakistan's urban markets are dominated by active users of AI in the working age group and higher education. The average of high daily usage (40.8%) and near daily usage (38.4%) suggests that the sample has a reasonable level of experience interacting with AI in daily life to provide meaningful measures of construct.

Confirmatory Factor Analysis and Measurement Model

Good overall goodness-of-fit in the CFA and construct validity were obtained. The measurement model fit indices and reliability and validity are presented in Table 2.

Construct / Fit Index	Items	Cronbach Alpha	CR	AVE	Mean	SD
AI-Powered Customer Experience	20	0.912	0.928	0.556	3.82	0.64
Personalization	14	0.887	0.904	0.534	3.69	0.69
Consumer Retention	10	0.864	0.882	0.514	3.64	0.71
CFI	0.954	—	—	—	—	—
TLI	0.947	—	—	—	—	—
RMSEA (90% CI)	0.051 (0.042-0.060)	—	—	—	—	—
SRMR	0.048	—	—	—	—	—
Chi-square/df	1.84	—	—	—	—	—

Table 2. Measurement model results: reliability, validity, and CFA fit indices.

CR = composite reliability; AVE = average variance extracted; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardised root mean square residual.

The model-data fit was adequate with all fit indices being above the thresholds: CFI = 0.954 (> 0.90); TLI = 0.947 (> 0.90); RMSEA = 0.051 (< 0.08 with narrow confidence interval); and SRMR = 0.048 (< 0.08). All constructs showed high level of internal consistency reliability ranging from 0.864–0.912 (cronbach alpha) and 0.882–0.928 (composite reliability), which is higher than 0.70. The Parallel Validity was examined by checking the AVE values and they were in the range 0.514-0.556 with the criterion of 0.50. Convergent validity of the items was confirmed with all factor loadings on the scales being > 0.50 (range 0.62-0.84; all p < 0.001).

Concurrent Validity

The results of the discriminant validity assessment and inter-construct correlation are shown in Table 3.

	AIPCE	PERS	CR	HTMT: AIPCE-PERS	HTMT: AIPCE-CR	HTMT: PERS-CR
AIPCE	0.745*	—	—	—	—	—
PERS	0.641**	0.731*	—	0.762	—	—
CR	0.569**	0.558**	0.717*	—	0.698	0.718

Table 3. Discriminant validity and correlation matrix

*Square root of AVE on diagonal. **p<0.001. HTMT values below 0.85 confirm discriminant validity. PERS = Personalization.

The square root of AVE values (diagonal) were greater than all inter-construct correlations which satisfied the Fornell-Larcker criterion. All HTMT ratios were less than 0.85 (range 0.698-0.762), indicating discriminant validity between pairs of constructs. The inter-construct correlations support theoretically proposed and reasonable moderate-to-high correlation levels (r = 0.558 – 0.641) while indicating no problematic multicollinearity.

Structural Model and Hypothesis Testing

Table 4 shows the relationship of SEM structural path coefficients and the model fitness statistics. The same CFA fit indices as for each measurement model were obtained for the structural model, indicating the appropriateness of each relationship specified.

Hypothesis	Structural Path	Std. Beta	SE	C.R.	p-value	f2	Result
H1	AIPCE -> PERS	0.641	0.046	13.93	<0.001	0.697	Supported
H2	AIPCE -> CR	0.298	0.059	5.05	<0.001	0.158	Supported
H3	PERS -> CR	0.421	0.054	7.80	<0.001	0.298	Supported
R2 (PERS)	0.411	—	—	—	—	—	—
R2 (CR)	0.623	—	—	—	—	—	—

Table 4. Structural equation model results: standardised path coefficients, standard errors, and critical ratios.

C.R. = critical ratio; f2 = Cohen effect size. PERS = Personalization.

All three hypothesised structural paths were statistically significant and in the predicted direction. The aforementioned support for high levels of personalisation theory, as per Personalization Theory, explained by AI powered customer experience quality being a significant driver of their perception of personalisation, was largely confirmed by the AIPCE-PERS path (which was the strongest in the model; beta = 0.641, f2 = 0.697; large effect). This confirmed the importance of personalisation in the retention of consumers with the PERS-CR path (beta = 0.421, f2 = 0.298, medium-to-large effect). When the mediator was added into the analysis, this direct AIPCE-CR path (beta = 0.298, f2 = 0.158, medium effect) was still present, showing partial mediation rather than full mediation. The structural model accounted for 62.3% variance in Consumer Retention (R2 = 0.623) showing good explanatory power.

Mediation Analysis and Sector Comparison

The results of mediation analyses and relative comparison of sectors are included in Table 5.

Analysis	Coefficient	SE	95% CI Lower	95% CI Upper	p-value	Notes
Total effect (AIPCE -> CR)	0.568	0.038	0.494	0.642	<0.001	—
Direct effect (AIPCE -> CR)	0.298	0.059	0.182	0.414	<0.001	—
Indirect via PERS	0.270	0.041	0.189	0.351	<0.001	VAF = 47.5%
Mediation type	Partial	—	—	—	—	—
PERS-CR beta: Streaming	0.486	—	—	—	<0.001	Highest

PERS-CR beta: Retailing	0.418	—	—	—	<0.001	Moderate
PERS-CR beta: Banking	0.341	—	—	—	<0.001	Lowest

Table 5. Mediation analysis results and sector-stratified Personalization-Retention path coefficients.

VAF = Variance Accounted For. Bootstrap n=5,000, bias-corrected CI.

The mediation process (through Personalization) was substantiated as the indirect effect of AIPCE on CR was significant (beta = 0.270, 95% CI: 0.189-0.351, excluding zero, $p < 0.001$). With a VAF of 47.5%, it shows that Personalization is a significant mediator, meaning it accounts for about 50% of the overall AIPCE-CR relationship, whilst the remaining direct pathway suggests a partial mediation as expected by theory, which suggests that AI experience quality contributes to retention via a personalisation-mediated pathway and a direct functional satisfaction pathway. The PERS-CR relationship was also found to be statistically significant when analysed using sector stratification, with streaming platform users exhibiting the strongest path (+0.486) as personalisation seems to be a key element of the streaming platform's value proposition. Retailing was associated with moderate personalisation-retention effects (beta = 0.418), and banking was associated with the weekest but still significant personalisation-retention path (beta = 0.341), possibly because the personalisation considerations of trust, security and reliability are more salient in banking terms.

Discussion

The results gathered in this study are highly powerful evidence of causality for the direct and indirect effect of customer experience on consumer retention as well as personalisation being used as a partial mediator, which was substantiated through the rigorous assessment of the measurement model for the instruments used, based on CFA, and using covariance-based SEM, the overall model explained 62.3% of the variance in Consumer Retention. Modeling directly addresses Perceived Personalisation through the mediation of the Customers' AI perceived experience of service (AL), revealing a large and significant direct effect of AIPCE on Perceived Personalisation (Beta = 0.641, large effect). This provides a confirmation of the relationship between experiential quality and service perception, which underpins the entire mediation pathway. This discovery has broadened the scope of Personalization Theory by empirically placing personalisation perception as an output and not as an independent variable thus evidentiating a psychological process through which AI systems create personalisation co-value to the customer.

The variability of this partial mediation is noteworthy as it empirically confirms the theoretically proposed mechanism whereby AI service quality leads to retention, which is, in reality, mediated primarily but not exclusively by personalisation (VAF = 47.5%). The presence of a strong direct path connecting AIPCE-CR in addition to the personalisation-mediated indirect path reflects that customer experience with AI has at least two entirely different satisfaction “sleeps”—a personalisation pathway where high-quality AIPCE influences personalisation perception which in turn affects the relational bond associated with the experience of retention, and a direct functional satisfaction pathway where positive AIPCE service experiences foster satisfaction with the service, that supports retention without the need for a personalisation perception. CRM Theory is consistent with this two-way view of customer retention which says that customer retention rests both on relational (personalisation mediated) and transactional (direct satisfaction) dimensions of the customer-provider relationship.

The personalisation-retention path coefficients show practically meaningful and tangible differences in the personalisation-retention mechanism by sector. In the streaming industry, the measure of personalisation quality best explains the value of the service offer, and will therefore have a stronger effect, as evidenced by the higher absolute values of beta, on the actual retention in this sector versus other sectors where the level of personalisation is one of several dimensions of service quality. The weaker but still significant banking personalisation-retention effect (beta = 0.341) suggests the multi-factor phenomenon of the banking choice of retention where perception of personalisation only contributes a part of the process behind retention, as other factors come into play as well, such as trust, security, accessibility and competitiveness of products. The implications of these sector differences are significant for investment in AI personalisation by sectors and for sector-specific retention strategies.

There are some limitations of the study. The cross-sectional design limits this study from being able to analyse the longitudinal dynamics of the relationship between AIPCE and Personalisation perceptions, and hence makes it difficult to assert that AIPCE has developed over time through interactions or that high-quality experiences are formed quickly. stratified sector sampling may not account for the full diversity of digital service consumers in Pakistan, which were affected by the convenience sample.The student enriched sample, although tempered by the stratified sector sampling design, is not necessarily a representative sample of the diversity of digital service consumers in Pakistan. Although theoretically suitable as a perceptive personalisation measure, the self-reported personalisation construct does not measure the objectiveness of the level of algorithmic personalisation adopted by the service providers and is thus a representation of the level of personalisation perceived by the user, and not of intensity. Future research could focus on longitudinal personalisation–repealationship dynamics and investigate the personalisation–retention link between personalisation parameters measured by technology and the perceived personalisation quality between industries.

Conclusion

It was widely believed that Personalization serves as a 'linkage mechanism,' between AI-Powered Customer Experience and Consumer Retention, but no study has yet tested this idea with empirical evidence supported by personalization theory and rigorously tested with CFA and covariance-based SEM analysis. The results validate previous research indicating that directly and indirectly through personalisation mediated pathways AIPCE was found to predict retention (beta = 0.298, indirect effect = 0.270, VAF = 47.5%, R2 = 62.3% for CR). The analysis of the sectors shows that the effects of personalisation on retention are most pronounced in streaming, being the services' main value proposition based on AI personalisation, most moderate in retail and banking contexts. The findings are a clear strategic recommendation for service managers - investment in experience quality via AI has a material impact on consumer retention, and in particular, personalisation-optimising AI systems have the highest possible impact on retention compared to other types; and the two pathways to consumer retention - directly vs. via the personalisation pathway - suggest that there is a need for both experience and personalisation service quality to be managed simultaneously.

Recommendations

AI Personalisation Strategy

In both a streaming context and a retail context, prioritise and focus the investment in personalisation, whereas in the banking context, balance the investment in personalisation with the improvement of the experience in terms of reliability and security, since the latter seems to be one of the aspects that weigh more in the decision.

Create AI personalisation architecture that maximises the customer's understanding of the relevance and signal dimensions of personalisation (not just the objectivity of the recommender accuracy metrics). Understand that personalisation perceptions that drive retention are psychological states that can be influenced by the communication that the personalisation stimuli represent, more than the accuracy of the personalisation objects itself.

CRM Integration

Use personalisation perception scores, recommendation acceptance rates, and personalisation-attributable repeat engagement rates alongside retention metrics as metrics on CRM performance dashboards, so that metrics on the personalisation pathway to retention will be available alongside the overall retention outcomes.

Decide on customer segmentation that separates customers with high personalisation value (where the PERS-CR pathway is most effective, and can give the customer the highest personalisation value for the personalisation invested), from those with high functional value of the service (where the pathway is through direct functional service quality) to enable different resource allocations for personalisation.

Future Research Directions

Longitudinal panel studies capturing the time variation at the AI experience-product quality, personalization-perception, retention-behaviour relationship over several service interaction cycles and examine if the strength of the relationship increases as the AI systems learn more from the behavioral data collected and enhance the quality of their personalised experiences over time.

Examine how information about other factors such as customer privacy concern, AI literacy, and demographic factors might moderate or change relationships between personalisation and retention, and explore how this impacts the targeting of personalisation-related retention efforts.

References

1. Arora, N., Dreze, X., Ghose, A., Hess, J. D., Iyengar, R., Jing, B., Joshi, Y., Kumar, V., Lurie, N., Neslin, S., Sajeesh, S., Su, M., Syam, N., Thomas, J., & Zhang, Z. J. (2008). Putting one-to-one marketing to work: Personalization, customization, and choice. Marketing Letters, 19(3-4), 305-321.

2. Epsilon. (2017). The power of me: The impact of personalization on marketing performance. Epsilon Data Management LLC.

3. Flavian, C., Ibanez-Sanchez, S., & Orus, C. (2022). The impact of virtual, augmented and mixed reality technologies on the customer experience. Journal of Business Research, 100, 547-560.

4. Gomez-Uribe, C. A., & Hunt, N. (2016). The Netflix recommender system: Algorithms, business value, and innovation. ACM Transactions on Management Information Systems, 6(4), 1-19.

5. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2-24.

6. Huang, M. H., & Rust, R. T. (2021). Engaged to a robot? The role of AI in service. Journal of Service Research, 24(1), 30-41.

7. Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. Journal of Marketing, 80(6), 69-96.

8. Linden, G., Smith, B., & York, J. (2003). Amazon.com recommendations: Item-to-item collaborative filtering. IEEE Internet Computing, 7(1), 76-80.

9. McKinsey & Company. (2021). The value of getting personalization right-or wrong-is multiplying. McKinsey & Company.

10. Mende, M., Scott, M. L., van Doorn, J., Grewal, D., & Shanks, I. (2019). Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. Journal of Marketing Research, 56(4), 535-556.

11. Ngai, E. W. T., Xiu, L., & Chau, D. C. K. (2009). Application of data mining techniques in customer relationship management: A literature review and classification. Expert Systems with Applications, 36(2), 2592-2602.

12. Payne, A., & Frow, P. (2005). A strategic framework for customer relationship management. Journal of Marketing, 69(4), 167-176.

13. Peppers, D., & Rogers, M. (1997). Enterprise one to one: Tools for competing in the interactive age. Currency Doubleday.

14. Reichheld, F. F. (1996). The loyalty effect: The hidden force behind growth, profits, and lasting value. Harvard Business School Press.

15. Tam, K. Y., & Ho, S. Y. (2006). Understanding the impact of web personalization on user information processing and decision outcomes. MIS Quarterly, 30(4), 865-890.

16. Tan, C., Liu, Q., & Zhou, N. (2021). How does artificial intelligence transform customer experience in banking services? Evidence from China. Journal of Retailing and Consumer Services, 61, 102539.

17. Tran, T. P., Mai, E. S., & Taylor, E. C. (2021). Engaging customers emotionally: The role of digital marketing communications in the customer experience journey. Journal of Research in Interactive Marketing, 15(4), 461-482.

18. Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. Journal of Marketing, 80(6), 97-121.

19. Zhang, Y., Ye, Q., & Law, R. (2019). Impacts of hotel attribute ratings on consumer satisfaction: A multilevel approach. Tourism Management, 32(4), 784-794.