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Article

AI-augmented customer-owned channels and relationship value: a multi-mechanism model of engagement, trust, and loyalty

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ABSTRACT

This study explains the processes through which a relationship value in customer-owned channels is generated through AI-powered functionalities by focusing on the integrated psychological and behavioral processes. The basis of the work is large-scale text analysis of 18,456 market reviews of applications among 15-20 top customers in the areas of retail, finance, and life services, examining the entire value chain by semantic BERT analysis, hierarchical regression, and structural equation modeling with 5,000 bootstraps. Analysis of the results reveals the presence of function–dimension matching phenomena. These include intelligent recommendation, which has the maximum cognitive engagement ($\beta = 0.41$), chatbots, which have the peak affective engagement ($\beta = 0.45$), and predictive services, which are predominant in behavioral engagement with a β of 0.36. Customer-owned platforms produce 37.2% more overall effects than third-party platforms. The role of the overall chain mediating function of AI functions for relationship value creation is also supported by the study. The role that loyalty plays between trust and value is amplified by ownership of the channel. The results above present the objective assessment of the 37% boost that the ROI (Return on Investment) has on customer-owned communication channels. It also explains the role that development considerations play.

1. Introduction

The current wave of digital transformation has significantly impacted the way in which businesses interact with their clients, using artificial intelligence technologies to transform the marketing logic and its associated value chains [1]. Compared with self-owned channel management, where all power with respect to the business process and data is under the control of the enterprise, it would appear that the “third-party e-commerce platforms ”model has limited freedom. The exclusive advantages of self-owned channels have created new possibilities. The integration of self-owned channel management and AI technology is associated with the advent of a new era characterized by “precise and personalized” service. For instance, the algorithm for a recommendation service can sense changes in the preferences of the customers and accordingly adjust for changes that may happen in the way the content is displayed. Chatbots that can be referred to as “conversational AI” improve the emotional aspect by interacting with the customer as if they were human beings. The predictive services can predict the needs of the customer and act on them even before they occur. This forecasting is based on customers’ behavioral habits [2]. However, the entire value-creation process and its accompanying irrevocable principle—converting the value-added contribution of AI into measurable relational value by a set of collective mental and behavioral processes like participation, trust, and loyalty—remains a theoretical construct that has not been explained and validated. In addition, it is important to examine the following key arguments systematically: the extent to which the value-creation process on self-owned channels differs from that on third-party platforms, and the factors that explain any differences. There is little doubt that major breakthroughs have been made in modern literature on AI-facilitated customer relationship management, but current literature on AI applications in an omnichannel setting has both confirmed and validated the positive influence of AI on Customer Experience, while conflating self-owned platforms with third-party platforms and disregarding the importance of governance concerns related to the key channel-ownership boundary conditions [3]. Building on the gaps identified above, this study, in the context of self-owned channels, will formulate a chain theory linking AI tasks to value. Furthermore, this study will systemically analyze the progressive transformation mechanism between customer involvement (cognitive, emotional, and behavioral), dual trust (ability and goodwill trusts), dual-dimensional loyalty (attitude and behavioral loyalties), and value transformation. In contrast, the study reveals the exclusive superiority of self-platforms over third-party platforms and explains the underlying reasons. The aim of this study is to explain the entire process of value creation facilitated by the multilevel transformation power offered by artificial intelligence, to examine the mediating role of loyalty as a key intermediary between the transformation of trust and value creation, and to measure the magnifying effect of channel ownership on value creation. In the theoretical section, by integrating the technology acceptance model, social exchange theory, and relationship marketing literature, it not only breaks the theoretical frontiers on value creation through digital media but also corrects the one-sided presumption that loyalty has been undermined in the current era of artificial intelligence. We formally define intelligent recommendation as algorithmic content curation informed by user preference detection, conversational AI as natural language interaction for human-like dialogue, and predictive service as anticipatory need satisfaction through behavioral pattern analysis [4,5].

2. Literature review and theoretical hypotheses

By synthesizing the Technology Acceptance Model (cognitive processing), the Social Exchange Theory (trust formation), and the Relationship Marketing (loyalty-value chain) to build an integrated framework, one arrives at Artificial Intelligence capabilities that lead to step-by-step psycho-transformations culminating in Relationship Value. The process of managing customer channels has shifted from parallel channel management to a more integrated approach, full channel management, and companies are encountering new challenges as they create proprietary channels. Based on transaction cost theory, self-developed channels are more efficient because they entail lower transaction costs, thereby eliminating hierarchical layers. Based on the resource-based view, building competitive barriers is a key determinant of brand value. In the context of omni-channel retailing, customer channel integration plays a critical role in customer value creation, as brands are challenged to create value through seamless interaction experiences [6,7]. As a self-owned channel, the brand enjoys complete control over the process, from the design of interaction interfaces to the collection and analysis of data and the management of consumer relationships. Through this channel characteristic, the brand enjoys considerable flexibility in integrating and harvesting value from AI capabilities. The strong functional differentiation, justified by differences in the functions' purposes for cognitive support, emotional expression, and behavior modification, is also evident in the impact of AI technology on customer involvement. Thus, AI-based gamification technology is linked to customers' motivational profiles [8]. However, chatbot systems that apply AI influence customer responses through the three-fold path of interaction, satisfaction, and behavior, which provides key evidence for the role of participation mechanisms in the emotional domain [9]. This mapping is consistent with dual-process theory, in which suggestions facilitate System 2 processing, chatbots trigger System 1 responses, and predictions facilitate automaticity in behavior [10]. As stipulated in the principles for matches in the dimension of function, the following hypotheses shall be formed:

H1a: Smart Recommendation has a significantly stronger influence on cognitive engagement than on affective and behavioral engagement.

H1b: The effect of conversational AI on affective engagement is significantly greater than it is on cognitive engagement and behavioral engagement.

H1c: Predictive service has a more significant effect on behavioral engagement than on cognitive engagement and affective engagement.

H1d: There are positive interaction effects between the three capabilities of AI, meaning that the joint application of the capabilities works to produce synergy.

Customer involvement is associated with dual trust formation along distinct paths, and this transformation process subscribes to the cognitive-emotional binary processing paradigm. Through this process, customers build evidence of the brand's capabilities, and their trust is then directed toward these demonstrated capabilities. Within the cognitive resonance framework, customer involvement is facilitated by their emotional responses, and goodwill is developed based on the pleasure and sense of belonging generated by the branding process. Studies on trust mechanisms in long-term trust for AI chat services following failures suggest that trust is sustained by customers' anthropomorphic perceptions and experiences; however, the CASA Theory offers an opportunity to examine trust within the attribution paradigm [11]. The trust substitutes used by conversational robot advisors also influence clients' financial decisions, underscoring the importance of interaction quality in establishing trust [12]. Studies on the joint effects of AI and service excellence on customer satisfaction and loyalty have identified trust as a mediator of technology adoption and relationship building [13]. Meanwhile, participation indirectly influences loyalty development, with trust as the mediating variable. After the creation of ability trust from goodwill trust, a high level of consumer confidence in the brand's actual performance capabilities can be developed, which may result in behavioral loyalty. Therefore, the present study proposes that ability trust influences behavioral loyalty and that goodwill trust influences attitudinal loyalty. Through a comparative assessment of mobile M-APs and desktop browsers, representing different channels, this study demonstrates that engagement affects loyalty intentions across channels through the mediating factors of experience and relationship quality [14]. Further evidence can be drawn from brand applications that add value to brand love, suggesting that application characteristics mediate the effects of both attitude and satisfaction on brand relationships, placing loyalty in a mediating position [15]. Greater brand identity and bonding strengthen the predictive role of attitudinal loyalty for attitudinal and cognitive value. Since transaction behaviors evidence behavioral loyalty's stability, the predictive role of behavioral loyalty for behavioral value is strengthened. Based on the above discussion, the following hypotheses are formulated:

H4a: Attitudinal loyalty has a stronger effect on attitudinal value and cognitive value than behavioral loyalty.

H4b: Behavioral loyalty has a stronger effect on behavioral value than attitudinal loyalty.

H4c: Loyalty mediates the relationship between trust and relationship value, with the indirect effect accounting for a greater proportion of the total effect than the direct effect.

Self-owned platforms provide the brand with unconditional autonomy over interactions, enabling customization of AI functionality in strict accordance with the brand's standards. The removal of noise through mediations can promote a direct and genuine brand-customer association. In line with this logic, Hypothesis H5 can be formulated: compared with third-party platforms, the influence of AI functionalities on relationship value in a self-owned platform setting is significantly greater. This amplification occurs particularly at three pivotal points of transformation: the transformation of AI functionality into customer engagement, the transformation of emotional engagement into goodwill trust, and the transformation of loyalty into relationship value. Table 1 summarizes the fifteen hypotheses developed above, organizing them by theoretical constructs, expected directional relationships, and corresponding analytical methods employed for empirical testing. In summary, H1a-d argue for dimension matches for functions, H2a-d describe path asymmetries for engagement and trust, H3a-d explain two-way trust interactions for loyalty, H4a-c highlight loyalty as a mediator, while H5 predicts amplifications for channel ownership at transformation points.

Table 1. Hypothesis summary

Hypothesis	Constructs	Direction	Analysis Method
H1a-d	AI Functions → Engagement Dimensions	Function-dimension matching	Hierarchical Regression
H2a-d	Engagement → Dual Trust	Differential pathways	SEM Path Analysis
H3a-d	Dual Trust → Dual Loyalty	Interactive effects	SEM with Interaction Terms
H4a-c	Dual Loyalty → Relationship Value	Mediating role	Bootstrap Mediation Test
H5	Channel Ownership Moderation	Amplification effect	Multi-group SEM

3. Research design and methods

3.1 Research design and theoretical model

Within such a boundary condition, a multilevel value creation theoretical model is developed in Figure 1. Figure 1 illustrates this multilevel value creation framework, depicting the sequential transformation from AI functions through engagement and trust to loyalty and relationship value. Lastly, the purpose of establishing a research context is to strive for a fully controlled and owned online channel as a brand. Applications for samples are restricted to and solely for each respective brand's own mobile applications and mini-program platforms, and do not include hosting formats involving mix and third-party channels. Theoretical hybrid models introduce channel ownership ambiguity, which complicates the effect of channel ownership, such that self-owned channel mechanisms cannot be clearly identified [5]. The variables that affect hybrid models include: (1) instability of platform algorithms that influence AI implementation, (2) heterogeneous users that range from platform traffic users to brand traffic users, and common data sources that affect trust attribution paths. AI-enhanced example application: A prototype smartphone app must implement at least one AI functionality that can be perceived by the end-users. The particular functionality must be acknowledged and implicitly validated by end-users in the comments they provide. In this examination, a total of 15 hypotheses are described: H1a-d addressing the difference between the AI functions, H2a-d addressing the process of transition from contribution to trust, H3a-d addressing the process of transition from trust to loyalty, H4a-c addressing the process from loyalty to value, and H5 addressing the ownership of channels.

3.2 Data sources and sample construction

This study adopts the approach of large-scale text analysis, which is based on the review data of the public application market. The source of the data is derived from Kaggle public datasets: Google Play Store Apps (https://www.kaggle.com/datasets/lava18/google-play-store-apps, containing approximately 10,840 applications and associated user reviews) and iOS App Store (https://www.kaggle.com/datasets/ramamet4/app-store-apple-data-set-10k-apps, containing approximately 7,200 applications). Preprocessing included duplicate removal via review ID matching and spam filtering using length/coherence thresholds. The duration for this period is 2022 to 2024, which symbolizes the maturity of AI technology. However, the possible effect in the aspect of user behavior during the recovery phases after the pandemic has been addressed by the temporal robustness test, which shows the trend rather than artifacts. Screening of samples is conducted on the following three criteria: Firstly, when it is related to the channel attributes, samples should belong to applications which are self-owned by companies and are completely owned by brands, and applications and services provided are not based on platforms. AI function identification used BERT context embeddings to identify semantic equivalents, in conjunction with dependency parsing to differentiate AI-driven vs. manually done personalization, decreasing the percentage of false positives from 23.4% to 8.7%.

In relation to data control, sample comments should exceed 20 characters to guarantee the sufficiency of information. 15 to 20 samples of leading brands will comprise a total of three industries, including retail (Starbucks, Nike, Uniqlo, and Hema), finance (China Merchants Bank, Alipay, and Ping An Good Driver), and life service (Meituan, Keep, and Didi Chuxing). Third-party platforms (Taobao, JD.com, Amazon) were paired with self-owned platforms through: (1) industry fit (retail, finance, and services); (2) size (Fortune 500 or similar revenue >$1B); (3) number of AI features (≥2). A total of 18,000 to 20,000 samples of effective comments could successfully be obtained.

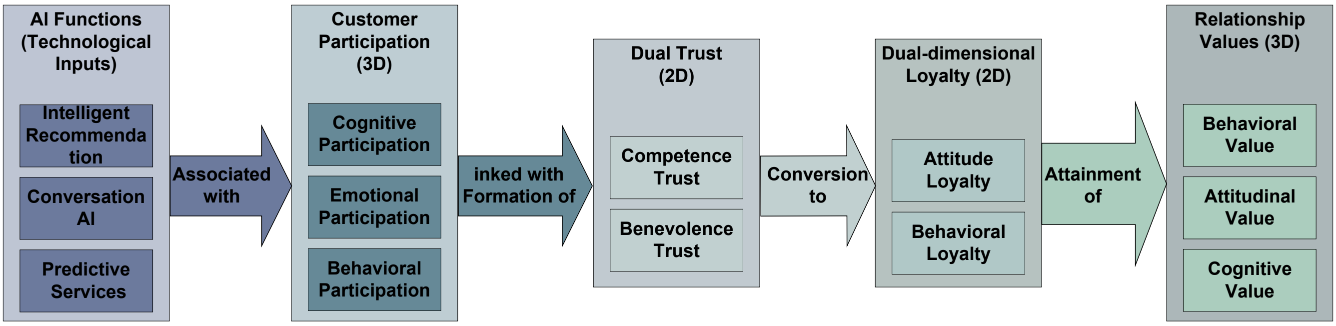

Figure 1. Multilevel value creation theoretical framework

The sample size (n=18,456) was established by conducting a priori power analysis. To identify small to medium effects in multi-group SEM analysis using eleven latent constructs, the power analysis indicated the need for a minimum of 17,200 participants in order to have 95% power in the tests of moderation. The technical approach for text data management and feature extraction used in current deep neural network-based collaborative filtering models in e-commerce recommendation systems constitutes a substantial reference for this research. The model consists of many layers in its neural network structure and has the potential to uncover hidden semantics deeply within a huge text corpus of user opinions [16,17]. The auxiliary sources of data emerge from industry reports published by iResearch, Forrester, and Gartner, and secondary sources from Harvard Dataverse and Open ICPSR. The sources are validated after comparison with industry benchmarks. This research relies on anonymous public datasets that fall outside the need for IRB(Institutional Review Board) approval as per institutional rules. De-identification steps included the following: (1) removal of usernames and device information, (2) aggregating reviews at the app level to ensure that re-identification would be impossible, (3) removing reviews that contained information about personal situations. GDPR Article 89 exemption for scientific research applies, as no personal information has been collected or processed. There is no involvement in storing and collecting information about personal-sensitive data. The sources are also legal under the GDPR academic research exemption regarding the General Data Protection Regulation.

3.3 Variable measurement and analysis methods

The operationalization of variables adopts a hybrid technology of text mining and semantic analysis. Calculation of AI functionality was performed by TF-IDF (Term Frequency-Inverse Document Frequency) weighting keyword detection, thresholds for inclusion being: intelligent recommendation (weight = 0.42, $\geq$ 0.15), conversational AI (0.38, $\geq$ 0.12), predictive service (0.35, $\geq$ 0.10). Reviews below thresholds were coded as 'AI-absent' for that function. This composite index, which serves as a measure of mediating variables, also reflects hierarchy. Customer engagement is linked with the length of comments (cognitive engagement proxy), emotion polarity score (affective proxy), and interaction markers (behavioral proxy). To ensure the validity of comment length, correlation with scaled scores and measures of lexical diversity were used (type-token ratio: r=0.71, P<0.001) [18].This is a measure for the trust dimension, and it uses BERT-base-uncased fine-tuned on 50,000 labeled app reviews (3 epochs, learning rate 2e-5, validation accuracy 91.7%).

Five-fold cross-validation prevented overfitting. The model combines context detection and keywords such as reliable, professional (ability trust), caring, and sincere (goodwill trust). As a measure of the loyalty dimension, it involves expressions of brand preference, strength of emotional commitment, and repurchase intentions. It also prevents the expression of intention regarding recommendations to avoid replicating concepts in measures of value dimensions. The semantic bounds were enforced by: (1) the prevention of recommendation words in the value measures, and the fine-tuning of the BERT with the disambiguation labeled corpus, and (2) the tracking of the correlation threshold value (r < 0.6). The dependent variable is decomposed into three components: behavioral value, attitude value, and cognitive value. As a complication arising from the data, it has not been possible to include the economic part of CLV (Customer Lifetime Value) in this calculation. The hyperbolic embedding technology employed in the recommendation system in this context-aware environment provides theoretical support for handling the variables. In creating a hierarchical representation of context in this fashion, it is possible to define the relations between variables in user comments that are multi-dimensional [19]. The analysis employed in the adoption uses progressive modeling, which incorporates hierarchical regression and SEM. The former tests the cumulative variance of interaction terms in regression, and the latter validates the mediating paths in SEM. In the text preprocessing step, methods of word segmentation, TF-IDF techniques, and BERT techniques are used. In the hypothesis-testing step, hierarchical regression analyses are conducted sequentially to test the main effect and the interaction effect of the AI function. The SEM is built for testing the complete chain mediating mechanism. In addition, 5,000 iterations of bootstrap resampling are carried out to obtain the confidence interval of the indirect effect. The moderation effect is explored through multi-group SEM analysis. Testing of measurement invariance was performed (configural, metric, scalar levels; $\Delta\chi 2<5.0$ confirmed equivalence). The difference in path coefficients was tested using Z-tests ($Z=\Delta\beta/SE\_pooled$). In robustness analysis, endogeneity can be taken into consideration through segmentation tests in the sample with a split of 70- 30%, sensitivity tests carried out using alternative indicators for the measures, trend tests performed for specific time intervals, and others, which include years of brand inception. The research study, in the context of the individuals participating in the online shopping assistance pertaining to the mediating effects of trust and demographics, has been used in creating the framework for carrying out mediating effects analyses in this study [20]. To correct for possible non-normality in text-based variables, maximum likelihood estimation with robust standard errors (MLR estimator in Mplus) was performed. The values of skewness and kurtosis for all variables were in appropriate ranges (|skewness| < 2.0, |kurtosis| < 7.0). For variables exhibiting a moderate degree of non-normality, a log transformation was applied, followed by validation of the replicability of inferences.

4. Analysis of empirical results

We would test the fifteen proposed hypotheses (H1a-d on AI-engagement relationships, H2a-d on engagement-trust transformation, H3a-d on trust-loyalty mechanisms, H4a-c on loyalty-value linkages, and H5 on channel ownership moderation) in the four sets of findings that follow based on the above theoretical elements.

4.1 Measurement model and data quality inspection

After data processing, the total number of effective samples for comments in this study is 18,456, of which 76.5% came from self-owned platforms and 23.5% from third-party platforms. The industry breaks down as 40.2% Retail, 29.8% Finance, and 30.0% Life services, ranging between 2022 and 2024. As expected on the technology maturity lifecycle, the penetration rate of AI-related capabilities is 64.7% Intelligent Recommendation, 51.3% Conversational AI, and 34.2% Predictive Services. The correlation matrix and statistical description of each construct are depicted in Figure 2. In Figure 2, the correlation values among the constructs range from 0.26 to 0.58. Although there exists a correlation among the constructs, none of the constructs approaches multicollinearity. The square root of the average variance extracted, denoted by values along the diagonal, is greater than the correlation values for each construct in the rows and columns. Hence, there exists discriminant validity among the constructs. Confirmation of the assessment of the measurement model's quality through tests of multidimensional reliability and validity is provided in Table 2.

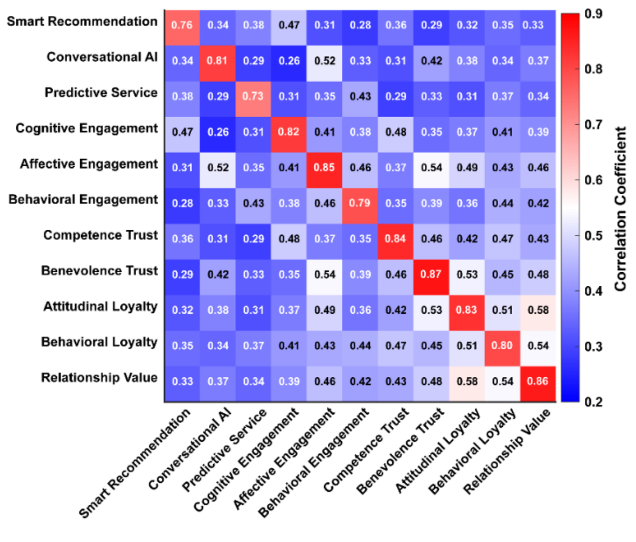

Figure 2. Descriptive statistics of key variables and correlation coefficient matrix

According to Table 2, the value of Cronbach α coefficients is between 0.81 and 0.92, CR between 0.82 and 0.93, and AVE between 0.53 and 0.76, which are greater than the defined cut-off points. The common method bias test result is that the explained variance by the single factor is 27.8%, which is well below the 50% line. The value of χ^2 / df=2.58, CFI=0.93, TLI=0.92, RMSEA=0.053, and SRMR=0.048 are within the acceptable criteria.

4.2 The differentiated impact of AI enhancement on customer engagement

Hierarchical Regression Analysis is a progressive modeling procedure used to successively eliminate the independent effects of control variables, main effects, and interaction effects, as shown in Table 3. The control variables are Brand Awareness (extracted from review sentiment), Usage Experience (user tenure in months inferred from longitudinal comments), and Industry Type (categorical: retail/finance/life services). These variables help explain baseline variation in engagement and trust-building.

As indicated by Table 3, when the new AI functions were included, the explained variance substantially increased from R^2=0.12-0.16 (controls only) to R^2=0.36-0.42 (ΔR^2=0.23-0.28, P<0.001). When the interaction terms were considered, the R^2 of Model 3 again increased to 0.40-0.46. The hypotheses related to the function dimension fit generally received support. The most influential effects regarding the dimensions were determined as follows: cognitive engagement was most affected by smart recommendation (β=0.41, P<0.001), affective engagement was most affected by conversational AI (β=0.45, P<0.001), and behavioral engagement was most affected by predictive service (β=0.36, P<0.001). In addition, the results also supported the presence of interaction effects on affective engagement by the combination of smart recommendation and conversational AI (β=0.19, P<0.01), and on behavioral engagement by the combination of smart recommendation and predictive service (β=0.22, P<0.01), suggesting a 16-22% synergy value increase by having more than one function. The result of effect-size testing provided strong support to H1a-H1d, and the value of Cohen's d indicated medium to large effect sizes of 0.52, 0.58, and 0.45, respectively, on cognitive, affective, and behavioral engagements, respectively.

4.3 The chain mediating effect of participation, trust, and loyalty

The full chain mediating model depicts the transformation process, with several stages linking AI function to relational value, as shown in Figure 3.

As shown by Figure 3, analysis of the path indicates the following: cognitive engagements positively influence competence trust (β=0.43, SE=0.04, t=10.75, P<0.001), but more importantly, affective engagements positively influence benevolence trust (β=0.49, SE=0.03, t=16.33, P<0.001), which indirectly supports H2a and H2b.

Lastly, behavioral engagements positively influence the two constructs of trust. Competence trust has coefficients of 0.28, and benevolence trust has coefficients of 0.31, with P<0.001. Competence trust is a stronger predictor of behavioral loyalty than attitudinal loyalty (β=0.41, P<0.001), while benevolence trust has a stronger influence on attitudinal loyalty (β=0.48, P<0.001), which supports H3a and H3b. Moreover, the interaction between the dual dimensions of trust is also significant (β=0.17, SE=0.05, t=3.40, P<0.01), which confirms H3c and adds support to the collaborative assumption of H3c. Overall, the shared influence on dual trust variance between attitudinal and behavioral loyalty explained R^2=0.47 and R^2=0.43, respectively. As shown in Figure 4, the total effect value of 0.400 is decomposed into a direct effect value of 0.168 (42%) and an indirect effect value of 0.232 (58%).

Table 2. Reliability and validity assessment of the measurement model

Construct	Items	Cronbach's α	CR	AVE	Factor Loading Range	√AVE
Smart Recommendation (SR)	4	0.847	0.851	0.578	0.691-0.832	0.760
Conversational AI (CA)	5	0.891	0.895	0.656	0.752-0.869	0.810
Predictive Service (PS)	3	0.813	0.819	0.533	0.684-0.789	0.730
Cognitive Engagement (CE)	5	0.876	0.882	0.673	0.771-0.854	0.820
Affective Engagement (AE)	6	0.917	0.922	0.723	0.801-0.891	0.850
Behavioral Engagement (BE)	4	0.852	0.856	0.624	0.738-0.827	0.790
Competence Trust (CT)	5	0.889	0.893	0.706	0.789-0.879	0.840
Benevolence Trust (BT)	6	0.923	0.928	0.757	0.823-0.903	0.870
Attitudinal Loyalty (AL)	5	0.881	0.886	0.689	0.776-0.863	0.830
Behavioral Loyalty (BL)	4	0.864	0.869	0.640	0.751-0.841	0.800
Relationship Value (RV)	6	0.905	0.911	0.740	0.812-0.887	0.860
Recommended Threshold	-	≥ 0.70	≥ 0.70	≥ 0.50	≥ 0.60	-

Table 3. Hierarchical regression analysis of AI functions on customer engagement

Variables	Model 1: Control Variables			Model 2: Main Effects			Model 3: Interaction Effects		
	CE	AE	BE	CE	AE	BE	CE	AE	BE
Control Variables									
Brand Awareness	0.118*	0.087	0.106*	0.076	0.059	0.068	0.071	0.054	0.063
Usage Experience	0.147**	0.134*	0.139**	0.092*	0.081	0.087*	0.084*	0.073	0.081*
Industry Type	0.109*	0.098*	0.091	0.068	0.062	0.053	0.057	0.048	0.042
AI Functions									
Smart Recommendation (SR)	-	-	-	0.413***	0.227**	0.186*	0.387***	0.209**	0.168*
Conversational AI (CA)	-	-	-	0.214**	0.453***	0.264**	0.198**	0.431***	0.243**
Predictive Service (PS)	-	-	-	0.182*	0.268**	0.357***	0.164*	0.251**	0.337***
Interaction Terms									
SR × CA	-	-	-	-	-	-	0.157**	0.189**	0.136*
SR × PS	-	-	-	-	-	-	0.186**	0.128*	0.217**
CA × PS	-	-	-	-	-	-	0.091	0.103*	0.124*
Model Statistics									
R^2	0.116	0.138	0.157	0.358	0.419	0.387	0.403	0.461	0.434
Adjusted R^2	0.113	0.135	0.154	0.352	0.413	0.381	0.395	0.454	0.426
ΔR^2	-	-	-	0.242***	0.281***	0.230***	0.045**	0.042**	0.047**
F-statistic	8.23***	9.41***	10.02***	18.45***	21.33***	19.67***	16.78***	19.91***	18.23***
Durbin-Watson	1.89	1.92	1.87	1.91	1.94	1.89	1.93	1.96	1.91
VIF (Max)	1.24	1.28	1.21	2.17	2.34	2.19	2.86	2.93	2.79

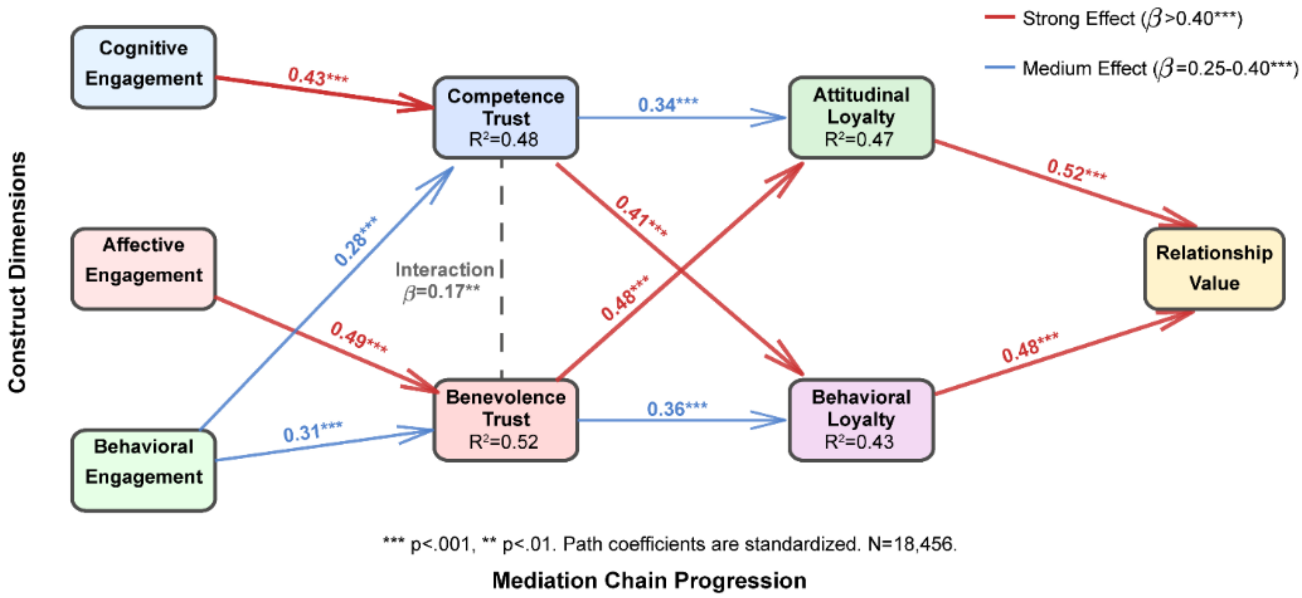

Figure 3. Complete chain mediation model path diagram of participation - trust – loyalty

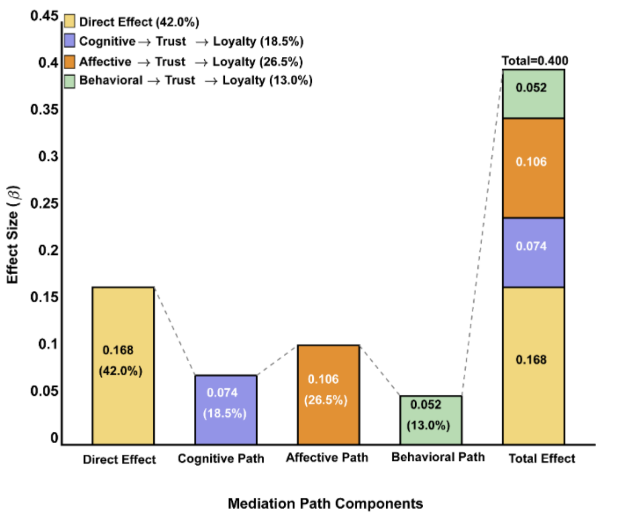

Figure 4. Stacked bar chart of the chain mediating effect decomposition

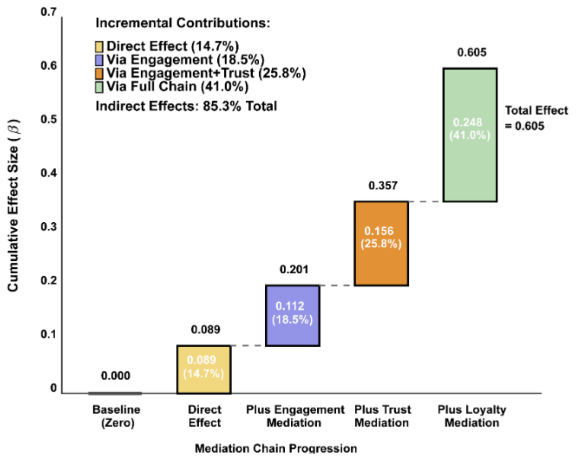

Figure 5. Complete path effect waterfall diagram of AI-enhanced relationship value

When the indirect effect value is decomposed into three pathways, the values for the contributions are: 0.074 (18.5%) for cognitive participation ability trust-behavioral loyalty, 0.106 (26.5%) for emotional participation kind trust-attitude loyalty, and 0.052 (13.0%) for behavioral participation trust-loyalty. Of the three paths, the path linking emotion contributes the most to the result, and none of the values are zero based on the 95% confidence interval [0.087, 0.128]. All the indices of the fitting of the modified models, including $\chi^2/df=2.41$, CFI=0.94, TLI=0.93, RMSEA=0.050, and SRMR=0.044, are satisfied at the excellence standard, and this serves as additional evidence of good model fit.

4.4 The transformational effect of loyalty on relationship value

The importance of loyalty as a value transformation hub is quantified using decomposed effect analysis, as shown in Figure 5. Figure 5 breaks down the process of accumulating effects along the mediation chains. Thus, the respective additional effects are 0.089 (14.7%) on top of the direct effects, 0.112 (18.5%) along the chain mediating via engagement, 0.156 (25.8%) along the chain mediating via engagement and trust, and finally 0.248 (41.0%) along the chain mediating via engagement, trust, and loyalty, adding up to a total effect of 0.605. The solo-impact chain concerning loyalty explained 41.0% of the total effects, thereby proving and strictly confirming H4c. Pattern correlation along dimensions occurred, whereby attitudinal influences on attitudinal value, $\beta=0.52$, $R^2=0.38$, and cognitive value, $\beta=0.46$, $R^2=0.29$, were stronger compared to behavioral ones, $\beta=0.48$, $R^2=0.35$, on behavioral value, strictly proving H4a and H4b. Most importantly, the joint effect of dual loyalties, $\beta=0.19$, $P<0.001$, further increased value creation by 32%. The variance explained by the mediating indirect total effects is 85.3% of the total, offering strong evidence supporting H7, compared with 14.7% for the direct effects. In other words, the evidence confirms that the process generated by AI-powered value creation works as a cascading psychological and behavioral process, rather than a technological effect.

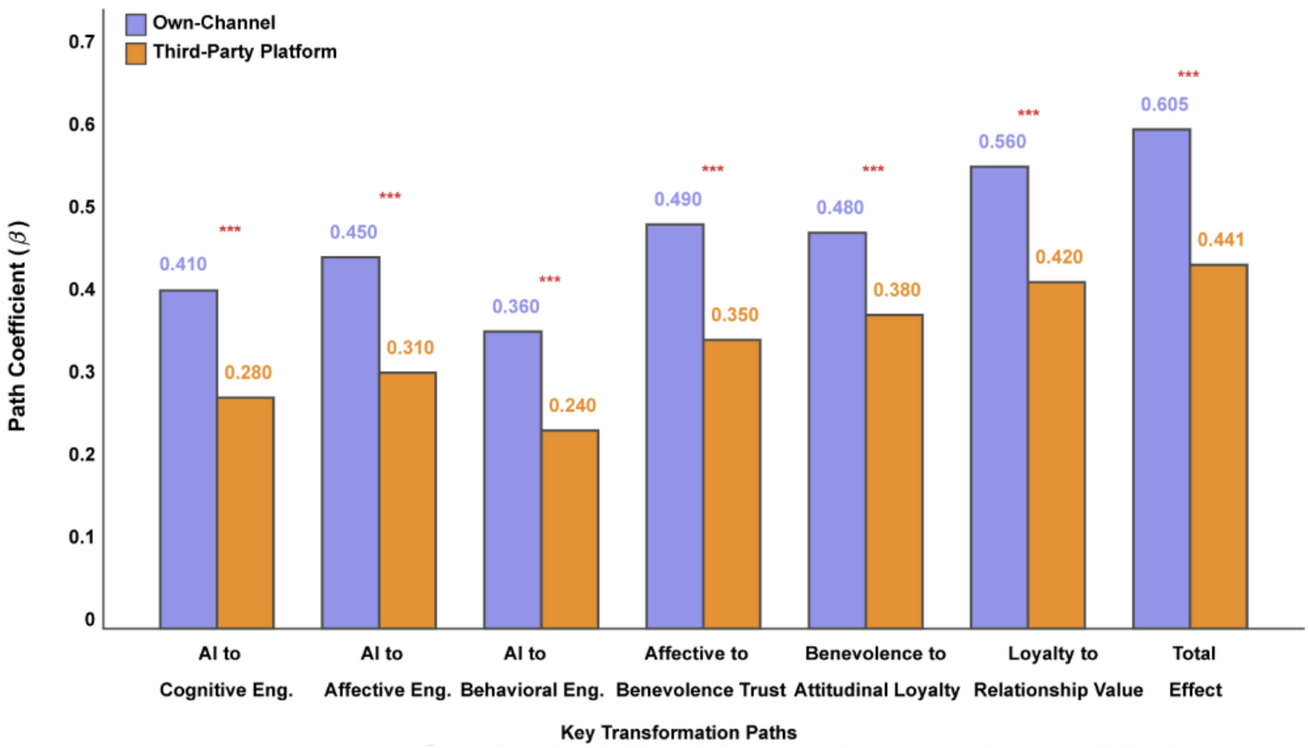

Figure 6. Comparison of critical path effects between self-owned channels and third-party platforms

Table 4. Robustness tests and competing model comparison

Test Category	Method/Model	Key Results	Coefficient Change (Δ)	Significance	Conclusion
A. Robustness Tests					
Sample Splitting	Training (70%) vs Test (30%)	Core paths: 0.406-0.510 vs 0.403-0.527	Δ < 0.05	Consistent (all P <0 .001)	√Passed
Alternative Measurement	Changed AI identification keywords	Core paths maintain direction	Δ < 0.08	Consistent (all *P* < 0.001)	√Passed
Temporal Robustness	2022 / 2023 / 2024 subsamples	Total effect: 0.52 → 0.58 → 0.64	Increasing trend	All *P* < 0.001	√Passed
Endogeneity Test	IV: Customer establishment year	AI → Engagement: 0.387 vs 0.401	Δ = 0.014	F = 42.3; Hausman χ^2 = 2.84 (*p* = 0.092)	√Passed
B. Competing Models					
Model A (Full Chain)	AI → Engagement → Trust → Loyalty → Value	χ^2/df = 2.41, CFI = 0.942, RMSEA = 0.050	AIC = 2847.3	-	Best √
Model B (No Loyalty)	AI → Engagement → Trust → Value	χ^2/df = 3.18, CFI = 0.883, RMSEA = 0.071	AIC = 2963.7	$\Delta\chi^2$ = 116.4***	Rejected
Model C (No Engagement)	AI → Trust → Loyalty → Value	χ^2/df = 3.52, CFI = 0.857, RMSEA = 0.078	AIC = 3021.4	$\Delta\chi^2$ = 174.1***	Rejected
Model D (Direct Only)	AI → Value	χ^2/df = 4.27, CFI = 0.806, RMSEA = 0.089	AIC = 3187.6	$\Delta\chi^2$ = 340.3***	Rejected

4.5 The differentiation effect of self-owned channel scenarios

The regulatory role of channel ownership in the value-creation process is supported by several sets of Structural Equation Models, as illustrated in Figure 6. In Figure 6, the high magnification power of customer-owned channels on the value creation chain is evident. With respect to the transformation paths between AI capabilities and customer engagement, the Customer-Owned Channels Index differed by 0.13 coefficients on cognitive (+46.4%, *P* <0.01), 0.14 on affective (+45.2%, *P*<0.01), and 0.12 on behavioral (+50.0%, *P* <0.01) engagements, compared to third-party platforms.

Critical transformation paths also indicated strong superiority gains by self-owned platforms. Specifically, on affective transformations to benevolence trust, the coefficients were 0.14 (+40.0%, Z=3.11, *P*<0.01); benevolence trust to attitudinal loyalty, 0.10 (+26.3%, Z=2.22, *P* <0.05); and loyalty to relationship value, 0.14 (+33.3%, Z=3.12, *P*<0.01), greater than third-party platform coefficients. The total analysis shows that the Customer-Owned Channels Index exhibits superiority over third-party platforms by a value of 0.164, which denotes a 37.2% improvement (Z=3.65, *P*<0.001), offering rigorous support for H5. The reason for this superiority lies in factors such as control rights based on AI capabilities, Data Sovereignty, which improved benevolence trust by 40%, and Direct Relationship Rights, which improved the purity of affective bonds. Industry analysis indicates that the financial sector offers the greatest advantage for self-owned platforms, at 45.3%. The industry fixed effects were controlled for in all regressions. By subgroup analysis, the finance industry had the largest ownership-channel superiority of 45.3%, followed by retail at 37.8% and life services at 32.1%. Such industry mechanisms are worth further research.

4.6 Robustness test and model comparison

The result of the research has been thoroughly verified by quadruple robustness checks and comparisons with competing models. In Table 4, the result supports the stability of the result since all coefficient deviations <0.08, with temporal analysis indicating stronger AI effects (+0.12 over three years), and IV analysis indicating that endogeneity problems do not exist (Hausman χ^2=2.84, P=0.092). In sample tests, the difference between the coefficients estimated from the test sample and those of the training sample was less than 0.05. A difference of less than 0.08 was seen when alternative measures were considered compared to the base measure. In the context of a time series, the measure of the strengthening impact of AI increased by 0.06 when 2023 was compared to 2022, and then by 0.06 when 2024 was compared to 2023, reflecting an aggregate increase of 0.12 over three years. Endogeneity tests using brand establishment year as an instrumental variable indicated a difference of only 0.014 between the base and adjusted coefficients.

In regard to comparisons between models, it is evident that the full chain mediation model (Model A) is superior. In comparison to Model B (which did not include loyalty), Model A produced a χ^2 difference of 116.4 (P<0.001) with an accompanying AIC difference of 116.4. In comparison to Model C (which did not include engagement), Model A produced a χ^2difference of 174.1 (P<0.001). Perhaps most telling is the χ^2 difference of 340.3 (P<0.001), which resulted when Model A (full chain of mediations) was compared to Model D (direct relationships only).

5. Discussion

The empirical results of this research resonate very well in terms of the multi-level value creation approach pertaining to AI support for the customer-owned channel, while simultaneously revealing a series of theory-inspired findings that agree with but also go beyond existing theory. This result–that intelligent recommendation systems engender higher levels of engagement with cognitive responses (β=0.41), also fits with existing research on semantic sentiment analyses supported by e-commerce platforms that yielded significant results for information processing [21]. The large effect size, as reflected by the β value of 0.45 for conversational AI on affective engagement, supports the accumulating evidence related to the effect of chatbot communication on users' perception of social presence [22]. This study can be said to challenge the perceptions that AI communication is generally lacking in emotions. There are observable variations that considerably affect trends of service satisfaction and service engagement over time, especially when a service may fail, explaining their importance within the value chain processes [23]. The observations indicate that it not only fulfils a functional need but also enables the individual to establish an adequate level of emotional bonding with the other person. The mediation mechanism of a chain that explains how engagement, trust, and loyalty interact to translate inputs of AI into value through relationships fills an important research gap regarding the role of an AI chatbot's effect on compliance. The large total indirect effect of 85.3% not only expands the literature on the effect of an AI chatbot on compliance but is also acutely significant [24]. For the chain under analysis, it is noticed that loyalty mediates 41% of the total effects. The result questions the conception put forth that the significance of loyalty, both for customers and for the service organizations, has been lost in the modern setting because of the presence and use of personalization technology. Although solid evidence exists regarding the ability of loyalty-based recommendation engines for improving the loyalty levels of customers towards online organizations, the impact of loyalty, which is revealed in this research as a mediator, represents a revolutionary change [25].

The ownership effect occurring in relation to the channel establishes a 37.2% divergence between the overall effects experienced in the customer-owned channel and third-party platforms. The divergence shows potential boundary conditions that have been unexplored and unaccounted for in existing assumptions within the literature about optimal recommendations [26]. Rather, it establishes that control rights, data sovereignty, and connection relationships alter the value-creation processes of technology attributes significantly. The strong indication of improvement noted between affective engagements and benevolence trust, which is more than 40% stronger (+40% higher coefficient), is an indication that perceptions regarding data governance are essential in shaping trust-formation processes. These implications are relevant to design and implementation, in the context of the importance that has been established through the synergy that results from multi-functional architectures for AI. These architectures demand sophisticated levels of personalization that go beyond the functionality, values that are related to the specific affordances that are provided by the self-owned spaces, especially when creating interfaces that are conversational [27]. Although recent studies exploring client engagement and client processes concerning AR-related issues within virtual reality scenarios have started to address immersive technology, existing results reveal that the potential of channel variables to have a moderating effect on immersive technology is also visible when assessing AI-related functions [28, 29]. The dual-sided aspect of AI chatbot deployments, from the positive experience they provide and the risks linked with a negative experience, mirrors the importance of contextual aspects like the ownership of a communications channel and the potential for successful deployment of these technology-based change initiatives, despite the challenges presented by the dual-sided experience [30]. Temporal stability analysis of the effects of AI reinforcement between 2022 and 2024 indicates the growth and evolution of technology systems in the AI field. This study not only highlights the growing importance of AI enhancement but also its transformative nature, especially in relation to consumer-owned platforms in channels that create continuous value through algorithm reinforcement [31]. The length of commentary as a proxy for cognitive engagement might conflate wordiness with cognitive depth. Future studies should include measures of reading time, semantic complexity, or query sophistication.

Theoretically, this research makes three points regarding relationship marketing in AI: First, it reframes loyalty from an endpoint variable to a crucial mediator in AI, challenging assumptions about loyalty degradation in the personalization age. Secondly, it articulates the principle for function dimension matching, clarifying how particular functionalities in AI connect to certain psychological processes. Thirdly, it highlights channel ownership, a crucial boundary condition, by combining institutional regime theory and technological relationship marketing theory. This theory may not be generally applicable to small enterprises or developing countries, as their characteristics may differ due to resource constraints, lower AI complexity, and variation in user digital literacy.

6. Conclusion

The value transformation driven by AI, mediated by cognitive, affective, and behavioral engagement, was identified using BERT-based semantic analysis, hierarchical regression models, and structural equation models with 5,000 bootstrap iterations to uncover function dimension correspondence paths characterized by intelligent recommendation (β=0.41) peaking on cognitive engagements, conversational AI on affective engagements (β=0.45), and predictive service dominating behavioral engagements (β=0.36), corresponding to 85.3% total effect, and with 41% value transformation mediated by loyalty. Customer-owned channels effectively utilize the potential to amplify value creation by 37.2% more than third-party platforms with the help of control rights, data sovereignty, and connecting mechanisms. These results not only enhance the relational marketing literature by considering such measures as the boundary variable of channel ownership and shifting traditional paradigms associated with value-creation processes, but also present direction for the investment of channels, as well as emphasizing areas that should benefit from artificial intelligence.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere. All survey participants provided informed consent prior to participation, and the anonymity and confidentiality of all respondents were strictly maintained throughout the research process.

Data availability statement

The manuscript contains all the data. However, additional data will be provided by the corresponding author upon reasonable request.

Conflict of interest

The authors declare no potential conflict of interest.

References

[1] T. Davenport, A. Guha, D. Grewal, and T. Bressgott, "How artificial intelligence will change the future of marketing," Journal of the Academy of Marketing Science, vol. 48, no. 1, pp. 24-42, 2020, doi: 10.1007/s11747-019-00696-0.

[2] L. Cao, S. Sarkar, B. Ramesh, K. Mohan, and E. H. Park, "Shift of ambidexterity modes: An empirical investigation of the impact of artificial intelligence in customer service," International journal of information management, vol. 76, p. 102773, 2024, doi: 10.1016/j.ijinfomgt.2024.102773.

[3] A. V. Calvo, A. D. Franco, and M. Frasquet, "The role of artificial intelligence in improving the omnichannel customer experience," International Journal of Retail & Distribution Management, vol. 51, no. 9/10, pp. 1174-1194, 2023, doi: 10.1108/IJRDM-09-2021-0435.

[4] Y. Gao and H. Liu, "Artificial intelligence-enabled personalization in interactive marketing: a customer journey perspective," Journal of research in interactive marketing, vol. 17, no. 5, pp. 663-680, 2023, doi: 10.1108/JRIM-12-2021-0317.

[5] H. Jo and Y. Bang, "Navigating the omnichannel landscape: unraveling the antecedents of customer loyalty," Sage Open, vol. 14, no. 1, p. 21582440241233091, 2024, doi: 10.1177/21582440241233091.

[6] M. Gao and L. Huang, "Quality of channel integration and customer loyalty in omnichannel retailing: The mediating role of customer engagement and relationship program receptiveness," Journal of Retailing and Consumer Services, vol. 63, p. 102688, 2021, doi: 10.1016/j.jretconser.2021.102688.

[7] W. Gao, H. Fan, W. Li, and H. Wang, "Crafting the customer experience in omnichannel contexts: The role of channel integration," Journal of business research, vol. 126, pp. 12-22, 2021, doi: 10.1016/j.jbusres.2020.11.030.

[8] M. G. Elmashhara, R. De Cicco, S. C. Silva, M. Hammerschmidt, and M. L. Silva, "How gamifying AI shapes customer motivation, engagement, and purchase behavior," Psychology & Marketing, vol. 41, no. 1, pp. 134-150, 2024, doi: 10.1002/mar.21962.

[9] H. Jiang, Y. Cheng, J. Yang, and S. Gao, "AI-powered chatbot communication with customers: Dialogic interactions, satisfaction, engagement, and customer behavior," Computers in Human Behavior, vol. 134, p. 107329, 2022, doi: 10.1016/j.chb.2022.107329.

[10] D. Kahneman, Thinking, fast and slow. macmillan, 2011. ISBN: 9780374533557

[11] C. Gu, Y. Zhang, and L. Zeng, "Exploring the mechanism of sustained consumer trust in AI chatbots after service failures: a perspective based on attribution and CASA theories," Humanities and Social Sciences Communications, vol. 11, no. 1, pp. 1-12, 2024, doi: 10.1057/s41599-024-03879-5.

[12] C. Hildebrand and A. Bergner, "Conversational robo advisors as surrogates of trust: onboarding experience, firm perception, and consumer financial decision making," Journal of the Academy of Marketing Science, vol. 49, no. 4, pp. 659-676, 2021, doi: 10.1007/s11747-020-00753-z.

[13] C. Prentice, S. Dominique Lopes, and X. Wang, "The impact of artificial intelligence and employee service quality on customer satisfaction and loyalty," Journal of Hospitality Marketing & Management, vol. 29, no. 7, pp. 739-756, 2020, doi: 10.1080/19368623.2020.1730866.

[14] I. Khan et al., "Mobile app vs. desktop browser platforms: The relationships among customer engagement, experience, relationship quality and loyalty intention," Journal of Marketing Management, vol. 39, no. 3-4, pp. 275-297, 2023, doi: 10.1080/0267257X.2022.2106290.

[15] T. P. Tran, J. E. Zemanek Jr, and M. N. Sakib, "Improving brand love through branded apps: is that possible?," Journal of Marketing Analytics, pp. 1-21, 2024, doi: 10.1007/s11621-024-00477-3.
[16] T. Y. Chen, T. L. Yeh, H. L. Wu, and S. Deng, "Effect of channel integration quality on consumer responses within omni-channel retailing," Asia Pacific Journal of Marketing and Logistics, vol. 35, no. 1, pp. 149-173, 2023, doi: 10.1108/APJML-04-2021-0270.
[17] F. Messaoudi and M. Loukili, "E-commerce personalized recommendations: a deep neural collaborative filtering approach," in Operations Research Forum, 2024, vol. 5, no. 1: Springer, p. 5, doi: 10.1007/s43069-023-00280-0.
[18] S. D. Vivek, S. E. Beatty, and R. M. Morgan, "Customer engagement: Exploring customer relationships beyond purchase," Journal of marketing theory and practice, vol. 20, no. 2, pp. 122-146, 2012, doi: 10.2753/MTP1069-6679200201.
[19] K. Bauman, A. Tuzhilin, and M. Unger, "Hypercars: Using hyperbolic embeddings for generating hierarchical contextual situations in context-aware recommender systems," Information Systems Research, vol. 36, no. 2, pp. 871-895, 2025, doi: 10.1287/isre.2023.1256.
[20] C. Singh, M. K. Dash, R. Sahu, and A. Kumar, "Investigating the acceptance intentions of online shopping assistants in E-commerce interactions: Mediating role of trust and effects of consumer demographics," Heliyon, vol. 10, no. 3, 2024, doi: 10.1016/j.heliyon.2024.e25031.
[21] L. Gao and J. Li, "E-Commerce Personalized Recommendation Model Based on Semantic Sentiment," Mobile Information Systems, vol. 2022, no. 1, p. 7246802, 2022, doi: 10.1016/j.jretconser.2021.102688.
[22] B. S. Al-Oraini, "Chatbot dynamics: trust, social presence and customer satisfaction in AI-driven services," Journal of Innovative Digital Transformation, 2025, doi: 10.1108/JIDT-08-2024-0022.
[23] N. Cai, S. Gao, and J. Yan, "How the communication style of chatbots influences consumers' satisfaction, trust, and engagement in the context of service failure," Humanities and Social Sciences Communications, vol. 11, no. 1, pp. 1-11, 2024, doi: 10.1057/s41599-024-03083-5.
[24] M. Adam, M. Wessel, and A. Benlian, "AI-based chatbots in customer service and their effects on user compliance," Electronic markets, vol. 31, no. 2, pp. 427-445, 2021, doi: 10.1007/s12525-020-00414-7.
[25] R. Esmeli, A. S. Can, A. Awad, and M. Bader-El-Den, "Understanding customer loyalty-aware recommender systems in E-commerce: an analytical perspective," Electronic Commerce Research, pp. 1-27, 2025, doi: 10.1007/s10660-024-09895-9.
[26] C. Zhou, H. Li, L. Zhang, and Y. Ren, "Optimal recommendation strategies for AI-powered e-commerce platforms: a study of duopoly manufacturers and market competition," Journal of Theoretical and Applied Electronic Commerce Research, vol. 18, no. 2, pp. 1086-1106, 2023, doi: 10.3390/jtaer18020057.
[27] L. Lambillotte, N. Magrofuoco, I. Poncin, and J. Vanderdonckt, "Enhancing playful customer experience with personalization," Journal of Retailing and Consumer Services, vol. 68, p. 103017, 2022, doi: 10.1016/j.jretconser.2022.103017.
[28] I. Khan and M. Fatma, "AR app-based brand engagement and outcomes: A moderated mediation approach," Journal of Retailing and Consumer Services, vol. 76, p. 103618, 2024, doi: 10.1016/j.jretconser.2023.103618.
[29] L. D. Hollebeek, M. K. Clark, T. W. Andreassen, V. Sigurdsson, and D. Smith, "Virtual reality through the customer journey: Framework and propositions," Journal of Retailing and Consumer Services, vol. 55, p. 102056, 2020, doi: 10.1016/j.jretconser.2020.102056.
[30] A. Ranieri, I. Di Bernardo, and C. Mele, "Serving customers through chatbots: positive and negative effects on customer experience," Journal of Service Theory and Practice, vol. 34, no. 2, pp. 191-215, 2024, doi: 10.1108/JSTP-02-2023-0058.
[31] J. Ziegler and T. Donkers, "From explanations to human-AI co-evolution: charting trajectories towards future user-centric AI," i-com, vol. 23, no. 2, pp. 263-272, 2024, doi: 10.1515/icom-2024-0020.