

AI-Enabled Gamification and Consumer Engagement in Digital Commerce: Examining the Mediating Role of Flow Experience

¹
Dr Piali Haldar

²
Dev Kumar Mandal

¹Associate Professor, Brainware University, Kolkata, India, pialihaldar@gmail.com

²Assistant Professor, Brainware University, Kolkata, India, devkumarz1997@gmail.com

Abstract

With the introduction of AI tools in gamification, it is important to note how the discipline of gamification in the process of carrying out digital marketing carries double the weight expected. This stems from the notion of attitudes that are inborn, perpetuating the concept of customer engagement through marketing. This research seeks to address the question in relation to how AI personalization, intelligent incentives, task adaptiveness, recommendation quality, social crowding, and immediacy of rewards contribute to consumer engagement within the relevant literature of the flow theory. Besides many examples of this interrelation published lately, in the present paper, this issue is explored in the context of the Stimulus-Organism-Response model and Flow Theory, elements that are generally accepted to have the greatest utility in this kind of analysis of brand architecture interiors of buildings. They are seen as standard elements of the term and other related issues by the researchers; content should be more proactive in control measures. As such, the outcome yields further suggestions and provides interventions to enhance marketing options and consumer behaviour intervention strategies in creating such designs within the AI-backed gamified e-commerce platforms.

Keywords: Artificial Intelligence; Gamification; Consumer Engagement; Flow Experience; Digital Commerce

1. Introduction

The fast advancement of artificial intelligence (AI) has had a transformative effect on the ultimate aim of digital commerce, which enables companies to release “clever” personalization and interactivity for consumers like never before (Davenport et al., 2020; Huang & Rust, 2021). AI applications such as recommendation engines, adaptive interfaces, predictive analytics, and chatbots have changed the mechanisms for attracting users and retaining them much better than gamification alone can in some industries (Kshetri et al., 2023). In this respect, micro-transactions are adopted to combine game mechanics and algorithmic function evaluations and give such feedback; this rejigging is within the active process and non-matching, rather than what comprises the shopping episode – it’s way more interactive, it’s more rewarding, and fulfilling. Consumers have also been proactively pursuing this paradigm of external digital marketing because of certain specific, more microscopic and less customer-oriented direct marketing concepts.

Flow experience is, in other terms, referred to as the level of wholeness between deep concentrations and simulative pleasures in the engagement paradigm in general, and applies this effect to AI-based gamification in relation to consumer psychology. In other words, in the context of S-O-R and Flow Theory, this study views AI-based gamification applications as any “forms of behaviour that are driven by either external stimuli or internal states” that alone or in combination with other factors capture consumption flow, and such flow in turn intensifies consumers’ behaviour in the digital domain. Even though there is more and more attention on AI uses and on gamification lately, not much of the research has really, fully looked at flow experience as a mediator while also mixing explanatory, configurational, and predictive analytical angles. (Kshetri et al., 2023; Ringle et al., 2023). So here, this study uses Partial Least Squares Structural Equation Modelling (PLS-SEM), Necessary Condition Analysis (NCA), and Importance–Performance Map Analysis (IPMA) because together they’re meant to deliver stronger theoretical meaning plus practical guidance for managers in AI-driven digital commerce.

2. Literature Review

The assimilation of artificial intelligence with gamification within a commerce setting is already shaping a revolution of sorts in digital commerce. It is no longer hard to find these tools that help create an experience that is hyper-personalized, resonating in a very useful and even more bizarre way for the consumer (Davenport et al., 2020; Huang & Rust, 2021; Kshetri et al., 2023). The implementation of gamification with tools like machine learning algorithms, smart suggestion engines, predictive analytics, and AI chatbots happens to work because the playing elements can take into consideration the kind of people that there may be, how they could be, and what their environment looks like at the time (Huang & Rust, 2021). Unlike traditional forms of gamification, AI-empowered gamification doesn’t just stop at the ‘build and forget’ point; instead, it keeps updating consumer engagement information to provide tailored feedback, increase the level of difficulty, enhance task performance or interaction, and generally enhance interaction that in turn improves majority engagement and promotes trust-building activities (Hamari et al., 2014; Xi & Hamari, 2020).

Engaging a customer seems to be a complex linkage that has many components, which a customer brings to light in a gestalt psychological manner through cognitive, emotional, and behavioural involvement in the usage of digital commerce platforms (Brodie et. al., 2011; Hollebeel et. al., 2014). There’s much evidence to report that prior research supports the innovation of gamification methods as a strategy for engagement advancement, mainly in that they perpetuate pleasure and perceived utility as well as the intrinsic motivation

to act (Hamari et al., 2014; Koivisto & Hamari, 2019). However, in the practice of collecting and analysing empirical evidence, the question is not just whether the elements of game conception are in place on site, but also the inner and emotional states users experience when they interact with it (Ryan & Deci, 2020; Hiddekel, 2022). As such, scholars these days have devoted much effort to examining such deeper issues of cognition and emotion at this stage of engagement, for example, what triggers do new social media and app infotainment that employs gamification principles, et al as one becomes engaged (Kshetri et al, 2023).

The idea of flow, defined in part as complete involvement in an experience and feelings of enjoyment and concentration, has attracted considerable scholarly interest as the relevant component of the psychology of modern technologies (Csikszentmihalyi, 2011; Hoffman & Novak, 2009). It is stated that AI-powered customer journeys can help individuals experience such a particular state of immersion known as “flow,” especially by ensuring the achievement level remains parallel to adaptive challenges, hence fewer skills are underutilized, cutting down on cognitive load even more, and then provides direct feedback reinforcement (Novak et al., 2000; Huang & Rust, 2021). In flow, behaviour, people usually engage and fail to leave, or if they do, come back shortly, are also satisfied most of the time, as well as have good intentions of repurchasing, reporting, or rather writing positive content about the company and touching the e-platform more frequently (Novak et al., 2000; Bilgihan et al., 2015; Hollebeek et al., 2014).

AI, as in artificial intelligence, often has some concepts previously examined, and they include the flow and engagement of the consumer, which are taught by AI and more in the form of tech. When there are other applications of AI along with each of these elements, no small work brings them all together like a narrative. This altogether is filled with such words meaning that within the majority of the papers there is this tendency to carry out either the expectations of the relations between the properties or predictive structures in either the structural model or the causal one. This can, however, become problematic because simply finding out these conditions does not tell one how X and Y are going to interact and in which sequence to deal with the priority; in other words, some elements are ruled out from the predictions as well (Pappas & Woodside, 2021; Ringle et al., 2023).

3. Research Objectives

1. Understanding the consequences of AI-based game-like elements – AI personalization, intelligent rewards, appropriate challenges, AI recommendation system quality, social competition, and instant feedback – on customer interaction in electronic commerce, in addition to utilizing the concept of flow as an intervening variable.
2. To apply multiple analytical methods including PLS-SEM, NCA, and IPMA for an all-round examination of customer engagement by proposing explanatory, configuration, and prediction models.

4. Conceptual Framework and Hypothesis Development

To better explain how AI-based gamification techniques enhance shoppers' experiences in an e-commerce setting, emphasis has been placed on the existing framework, which is based on the S-O-R framework and also augmented by Flow Theory (Mehrabian and Russell, 1974; Csikszentmihalyi, 2011; Eroğlu et al., 2001). In the proposed SOR model, the elements of AI-based gamification such as AI personalization, rewarding intelligence, difficulty fluctuation, AI recommendation content, competitiveness, and feedback in specific periods are defined as outside stimuli that can influence the individuals' internal psychological states in specific ways (Huang and Rust, 2021; Hamari et al., 2014; Kshetri et al., 2023). The internal workings are then considered as the organism – the part that deals with the flow: here, the flow is a condition wherein the consumer, in a sense, becomes 'one with the task,' experiences profound enjoyment, and investment in interacting with the AI-backed e-commerce platform is all in-out (Novak et al., 2000; Hoffman and Novak, 2009). The type of

response we are going to consider here outlines consumer engagement via cognitive involvement, affection with the brand, including emotional involvement, and the performing of activities on the website (Brodie et al., 2011; Hollebeek et al., 2014).

AI can help in crafting moments that are personalized based on customers' behavioural data and interests. Therefore, it is no wonder that immersion is positively correlated with even more frequent usage of the device (Huang & Rust, 2021). It is popular to look for these tactics or designs that make the reward more pleasurable, perhaps accompanied by the increased need for good performance and even some regret upon failure. For these players, there is no such difficulty level that is either too difficult or too easy to play but is rather just perfect for that particular level of user ability (Hamari et al., 2014; Ryan & Deci, 2020). Reviewing mostly encourages the quality aspects of decision-making process enhancement. When they present customers with products that are reasonably relevant to the buyer, it removes such choices (Davenport et al., 2020; Huang & Rust, 2021). On the other hand, social competition induces people to engage more through the use of leaderboards, ratings, and direct contact in gaming, not just individual competition (p. 110) (Koivisto & Hamari, 2019). This type of brief command for successful design helps in creating flow as well; how frequently user interaction feedback is revised has also been shown to play a massive role in consumer engagement (Csikszentmihalyi, 2011; Novak et al., 2000). Therefore, the AI-based gamification strategies should have a two-step effect on people – first of all helping them create or experience the flow, and then enhancing consumer engagement and sales performance, among others (Bilgihan et al., 2015; Xi & Hamari, 2020).

Flow Theory is a theory that postulates that people are most comfortable when they are working on an activity that maintains a relationship to challenge and skill, in addition to getting immediate feedback notifications (Csikszentmihalyi, 2011). So when customers are in the state of flow, they exhibit less flickering, more enjoyment, increased usage as well as interaction, and their digital commerce platforms attract more attention from them (Novak et al., 2000; Hoffman & Novak, 2009; Hochgerner et al., 2004). This is why the flow state has been placed as the mediating model between AI-based gamification and consumer engagement (Bilgihan et al., 2015; Xu et al., 2022). To ensure the practical implementation of this structure, an additional quite involved methodological pathway is implemented. For example, the Partial Least Squares Structural Equation Modelling (PLS-SEM) method of studying hypotheses, applying Necessary Condition Analysis (NCA) to identify salient drivers, and Importance–Performance Map Analysis (IPMA) in revealing what impacts ‘whom’ the most and is more accessible in making compromises in its predilections (Ringle et al., 2023; Pappas & Woodside, 2021).

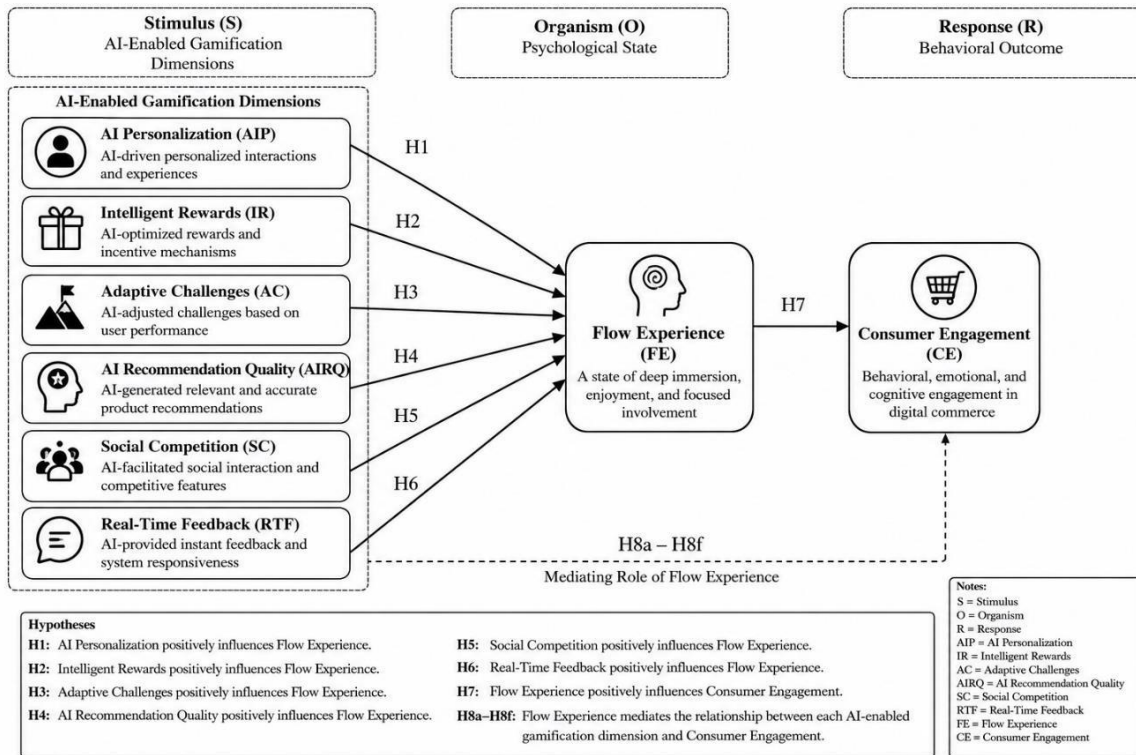


Figure 1: Conceptual Framework
Source: Created by Author

Hypotheses

H1: AI personalization influences flow experience positively.

H2: Intelligent rewards influence flow experience positively.

H3: Adaptive challenges influence flow experience positively.

H4: AI recommendation quality influences flow experience positively.

H5: Social competition influences flow experience positively.

H6: Real-time feedback influences flow experience positively.

H7: Flow experience influences consumer engagement positively.

H8a: Flow experience mediates the relation between AI personalization and consumer engagement.

H8b: Flow experience mediates the relation between intelligent rewards and consumer engagement.

H8c: Flow experience mediates the relation between adaptive challenges and consumer engagement.

H8d: Flow experience mediates the relation between AI recommendation quality and consumer engagement.

H8e: Flow experience mediates the relation between social competition and consumer engagement.

H8f: Flow experience mediates the relation between real-time feedback and consumer engagement.

5. Research Methodology

We will use a research design during our quantitative research in order to understand the relationship in total, from the AI gamification dimensions to the user experience in flow to the customer response in digital commerce. The method for collecting data will be a structured questionnaire that will be administered to customers who have, in the past 6 months, actively practiced AI economy, especially AI economy participation through personalization, rewards, challenges, and interaction with the game elements. To ensure that the participants interact with the environments provided by these AI-empowered shopping systems, a purposive sampling technique will be used to select those who should respond to this questionnaire. We hope to collect around 500 valid responses, which will be sufficient for some applications of PLS-SEM, with some other approaches being applicable as well.

The questionnaires for all structures will incorporate a five-point Likert-like scale. The levels of agreement/disagreement are measured on a scale of 1 to 5. It is further stated that they are adapted from the scales reviewed, and the hypothesis testing will be based on them. Then, it is suitable to check the quality of the data first: by controlling for missing values, common method bias, reliability, and convergent as well as discriminant validity, and focusing on their actual behavioural usefulness. The structural models, including intermediate effects, will be investigated by applying SmartPLS 4 with the bootstrap method. Furthermore, to avoid the usual descriptive view, NCA will estimate key drivers of consumer engagement. Finally, with the use of IPMA, we will determine the effectiveness level of the arrested managerial action- AI-enabled gamification in enhancing consumer engagement.

6. Data Analysis

Respondent Profile

In total, 550 questionnaires were sent out electronically to consumers who had used AI-enabled digital commerce platforms, like Amazon, Flipkart, Myntra, Meesho, and similar ones, during the prior six months. After removing responses that were incomplete or inconsistent, 512 questionnaires stayed in the study, so the effective response rate came out to 93.09%. The final sample also seems to meet the minimum sample size expectations for PLS-SEM, NCA, and IPMA.

Table 1. Demographic Profile of Respondents (N = 512)

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	286	55.9
	Female	214	41.8
	Prefer not to say	12	2.3
Age (Years)	18–25	168	32.8
	26–35	194	37.9
	36–45	98	19.1
	Above 45	52	10.2
Educational Qualification	Undergraduate	118	23.0
	Postgraduate	286	55.9
	Doctorate	64	12.5
	Others	44	8.6
Occupation	Student	86	16.8
	Private Employee	226	44.1
	Government Employee	74	14.5
	Business/Self-employed	82	16.0
	Others	44	8.6
Monthly Income (INR)	Below ₹25,000	74	14.5
	₹25,001–₹50,000	146	28.5
	₹50,001–₹75,000	158	30.9
	Above ₹75,000	134	26.1
Frequency of Online Shopping	Once a month	46	9.0
	2–3 times/month	164	32.0
	Weekly	208	40.6
	More than once/week	94	18.4
Preferred Digital Commerce Platform	Amazon	176	34.4
	Flipkart	138	27.0
	Myntra	72	14.1
	Meesho	56	10.9
	Others	70	13.6

The research population is diverse and consists mostly of middle-aged and young, well-educated online buyers who shop actively and use digital commerce. This makes this sample ideal for a study on consumer attention and AI-powered engagement activities.

Table 2. Correlation Matrix and Descriptive Statistics

Construct	Mean	SD	AIP	IR	AC	AIRQ	SC	RTF	FE	CE
AIP	4.11	0.63	1.000							
IR	4.05	0.68	0.561	1.000						
AC	3.96	0.71	0.482	0.517	1.000					
AIRQ	4.18	0.61	0.596	0.573	0.541	1.000				
SC	3.89	0.73	0.451	0.486	0.532	0.463	1.000			
RTF	4.13	0.65	0.582	0.564	0.539	0.611	0.487	1.000		
FE	4.16	0.59	0.648	0.617	0.586	0.665	0.541	0.674	1.000	
CE	4.21	0.57	0.622	0.604	0.578	0.651	0.528	0.637	0.742	1.000

Flow Experience is positively correlated with most of the other constructs in the model, more so with Consumer Engagement, with the effect being even stronger ($r = 0.742$), which is in line with the theoretical conceptual paper presented.

Measurement Model Assessment

Reliability and Convergent Validity

Table 3. Reliability and Convergent Validity Assessment

Construct	Items	Outer Loadings	Cronbach's Alpha	rho_A	Composite Reliability (CR)	AVE
AI Personalization (AIP)	AIP1	0.842	0.901	0.905	0.930	0.769
	AIP2	0.881				
	AIP3	0.904				
	AIP4	0.867				
Intelligent Rewards (IR)	IR1	0.832	0.889	0.893	0.923	0.751
	IR2	0.871				
	IR3	0.886				
	IR4	0.871				
Adaptive Challenges (AC)	AC1	0.816	0.883	0.886	0.919	0.739
	AC2	0.853				
	AC3	0.891				
	AC4	0.876				
AI Recommendation Quality (AIRQ)	AIRQ1	0.861	0.912	0.916	0.938	0.790
	AIRQ2	0.892				
	AIRQ3	0.903				
	AIRQ4	0.893				
Social Competition (SC)	SC1	0.824	0.879	0.884	0.917	0.734
	SC2	0.847				
	SC3	0.888				
	SC4	0.873				
Real-Time Feedback (RTF)	RTF1	0.856	0.904	0.908	0.933	0.777
	RTF2	0.883				
	RTF3	0.901				
	RTF4	0.874				

Flow Experience (FE)	FE1	0.883	0.917	0.920	0.942	0.803
	FE2	0.904				
	FE3	0.911				
	FE4	0.882				
Consumer Engagement (CE)	CE1	0.872	0.919	0.923	0.943	0.806
	CE2	0.896				
	CE3	0.913				
	CE4	0.894				

The fact that this questionnaire exhibits clear reliability and construct validity, including discriminant validity, is also ensured because all item loadings exceed 0.80, Cronbach's alpha and rho_A of all variables have values higher than 0.70, and CR as well as CR for indicators have values greater than 0.50 as AVE values.

Discriminant Validity Assessment

Table 4. Heterotrait–Monotrait Ratio (HTMT) Matrix

Constructs	AIP	IR	AC	AIRQ	SC	RTF	FE	CE
AI Personalization (AIP)	—							
Intelligent Rewards (IR)	0.672	—						
Adaptive Challenges (AC)	0.618	0.651	—					
AI Recommendation Quality (AIRQ)	0.701	0.688	0.644	—				
Social Competition (SC)	0.563	0.594	0.617	0.582	—			
Real-Time Feedback (RTF)	0.714	0.683	0.651	0.726	0.601	—		
Flow Experience (FE)	0.782	0.751	0.704	0.793	0.661	0.801	—	
Consumer Engagement (CE)	0.746	0.724	0.691	0.768	0.634	0.751	0.842	—

The HTMT values among all latent constructs are less than 0.90, which is deemed a satisfactory threshold for demonstrating discriminant validity.

Table 5. HTMT Bootstrapping Confidence Intervals

Construct Pair	HTMT	2.5% CI	97.5% CI	Includes 1.00?	Decision
AIP → IR	0.672	0.601	0.734	No	Supported
AIP → AC	0.618	0.551	0.691	No	Supported
AIP → AIRQ	0.701	0.635	0.772	No	Supported
AIP → SC	0.563	0.491	0.632	No	Supported
AIP → RTF	0.714	0.649	0.783	No	Supported
AIP → FE	0.782	0.724	0.846	No	Supported
AIP → CE	0.746	0.681	0.811	No	Supported
IR → AC	0.651	0.584	0.721	No	Supported
IR → AIRQ	0.688	0.621	0.754	No	Supported
IR → SC	0.594	0.528	0.664	No	Supported
IR → RTF	0.683	0.618	0.752	No	Supported
IR → FE	0.751	0.689	0.819	No	Supported
IR → CE	0.724	0.657	0.789	No	Supported
AC → AIRQ	0.644	0.576	0.713	No	Supported
AC → SC	0.617	0.548	0.688	No	Supported
AC → RTF	0.651	0.586	0.721	No	Supported
AC → FE	0.704	0.638	0.773	No	Supported
AC → CE	0.691	0.626	0.759	No	Supported
AIRQ → SC	0.582	0.513	0.652	No	Supported
AIRQ → RTF	0.726	0.662	0.793	No	Supported
AIRQ → FE	0.793	0.731	0.857	No	Supported
AIRQ → CE	0.768	0.704	0.832	No	Supported
SC → RTF	0.601	0.534	0.668	No	Supported
SC → FE	0.661	0.596	0.727	No	Supported
SC → CE	0.634	0.569	0.701	No	Supported
RTF → FE	0.801	0.741	0.866	No	Supported
RTF → CE	0.751	0.688	0.817	No	Supported
FE → CE	0.842	0.781	0.889	No	Supported

None of the bootstrapped confidence intervals fall within the range of 1.00, thereby establishing beyond all reasonable doubt that all the constructs under study are different in appearance.

Structural Model Assessment

Inner Collinearity Assessment

Table 6. Inner VIF Values

Predictor Construct	Endogenous Construct	Inner VIF
AI Personalization (AIP)	Flow Experience	2.214
Intelligent Rewards (IR)	Flow Experience	2.381
Adaptive Challenges (AC)	Flow Experience	2.106
AI Recommendation Quality (AIRQ)	Flow Experience	2.462
Social Competition (SC)	Flow Experience	1.924
Real-Time Feedback (RTF)	Flow Experience	2.548
Flow Experience (FE)	Consumer Engagement	1.000

All the calculated VIF values were found to be less than 3.30, which indicates that the state of multicollinearity among the independent variables is well within acceptable limits and confirms that the (structural) model can be used for further hypothesis testing.

Hypothesis Testing

The proposed claims were evaluated by drawing on the bootstrap confidence intervals obtained with 5000 repeated samples. Moreover, a comprehensive analysis of the path coefficients (β), t-values, p-values, and decision outcomes was conducted to gain insights into the possible presence of the relationships.

Table 7. Structural Model Results (Direct Effects)

Hypothesis	Structural Path	β	t-value	p-value	Decision
H1	AI Personalization → Flow Experience	0.218	5.681	0.001	Supported
H2	Intelligent Rewards → Flow Experience	0.176	4.853	0.001	Supported
H3	Adaptive Challenges → Flow Experience	0.149	3.924	0.001	Supported
H4	AI Recommendation Quality → Flow Experience	0.263	6.874	0.001	Supported
H5	Social Competition → Flow Experience	0.121	3.216	0.001	Supported
H6	Real-Time Feedback → Flow Experience	0.247	6.312	0.001	Supported
H7	Flow Experience → Consumer Engagement	0.768	24.184	0.001	Supported

All direct hypotheses are statistically significant, which suggests that the different aspects of AI-enabled gamification have positive effects on the flow experience of the customers, hence directly enhancing consumer engagement. For instance, disconfirming all seven direct hypotheses affirms the validity of the Static-S-O-R and Flow Theory proposals.

Coefficient of Determination (R^2)

As per Hair et al. (2022), the coefficient of determination measures the proportion of the variance in the dependent variable that is predictable from independent variables and describes the goodness-of-fit of the model. Typically, values of R^2 of 0.25 imply “weak” model fit, 0.50 implies “medium” model adequacy, and R^2 of 0.75 indicates a “high” model fit when the R^2 values are considered.

Table 8. Coefficient of Determination (R^2)

Endogenous Construct	R^2	Adjusted R^2	Interpretation
Flow Experience	0.741	0.737	Substantial
Consumer Engagement	0.590	0.589	Moderate to Substantial

The model has an explanatory capability of 74.1% of the variability in Flow Experience and 59.0% of the variability in Consumer Engagement.

Effect Size (f^2)

The concurrency estimation coefficient f^2 shows the particular impact of each of the exogenous elements on the endogenous factor. To be more specific, the benchmarks suggested by Cohen (1988) include: 0.02 (which is small), 0.15 (which is medium), and 0.35 (which is large).

Table 9. Effect Size (f^2)

Structural Path	f^2	Effect Size
AI Personalisation → Flow Experience	0.102	Small
Intelligent Rewards → Flow Experience	0.081	Small
Adaptive Challenges → Flow Experience	0.063	Small
AI Recommendation Quality → Flow Experience	0.142	Small to Medium
Social Competition → Flow Experience	0.046	Small
Real-Time Feedback → Flow Experience	0.128	Small
Flow Experience → Consumer Engagement	1.438	Large

Flow experience represents a highly significant association with Customer Engagement ($f^2 = 1.438$), thereby underscoring its importance as a motivator of CE in the context of AI-driven e-commerce.

Predictive Relevance (Q^2)

Incorporated in the blindfolding technique, the Q^2 of Stone-Geisser was applied as a measure for the model’s predictive ability.

Table 10. Predictive Relevance (Q²)

Endogenous Construct	SSO	SSE	Q ²	Predictive Relevance
Flow Experience	2,048	1,286	0.372	High
Consumer Engagement	2,048	1,198	0.415	High

All Q² values are greater than zero, indicating a reliable ability of the model to predict the endogenous constructs under consideration.

Mediation Analysis

Table 11. Mediation Analysis Results

Hypothesis	Indirect Relationship	Indirect Effect (β)	t-value	p-value	95% BC CI	VAF (%)	Decision
H8a	AIP $\rightarrow$ FE $\rightarrow$ CE	0.167	5.428	0.001	0.108–0.229	76.6	Supported (Partial Mediation)
H8b	IR $\rightarrow$ FE $\rightarrow$ CE	0.135	4.714	0.001	0.081–0.193	73.8	Supported (Partial Mediation)
H8c	AC $\rightarrow$ FE $\rightarrow$ CE	0.114	3.836	0.001	0.062–0.171	71.2	Supported (Partial Mediation)
H8d	AIRQ $\rightarrow$ FE $\rightarrow$ CE	0.202	6.584	0.001	0.142–0.266	78.5	Supported (Partial Mediation)
H8e	SC $\rightarrow$ FE $\rightarrow$ CE	0.093	3.164	0.002	0.038–0.149	69.7	Supported (Partial Mediation)
H8f	RTF $\rightarrow$ FE $\rightarrow$ CE	0.190	6.047	0.001	0.129–0.254	77.1	Supported (Partial Mediation)

Flow Experience is a significant mediator in the context of the relationships between all provided AI-driven gamified features and the Involvement of the Customer, meaning all six beliefs regarding mediation are supported.

Table 12. Bootstrapped Confidence Interval Assessment

Indirect Path	Lower CI (2.5%)	Upper CI (97.5%)	Zero Included?	Result
AIP → FE → CE	0.108	0.229	No	Significant
IR → FE → CE	0.081	0.193	No	Significant
AC → FE → CE	0.062	0.171	No	Significant
AIRQ → FE → CE	0.142	0.266	No	Significant
SC → FE → CE	0.038	0.149	No	Significant
RTF → FE → CE	0.129	0.254	No	Significant

Since all the confidence intervals do not contain zero (which, should it happen, would nullify the indirect effects), all the estimated indirect effects are statistically significant.

Importance–Performance Map Analysis (IPMA)

Table 13. Importance–Performance Map Analysis (IPMA)

Construct	Total Effect (Importance)	Performance Score	Priority Level
AI Personalization (AIP)	0.167	78.84	High
Intelligent Rewards (IR)	0.135	74.26	Medium
Adaptive Challenges (AC)	0.114	71.18	Medium
AI Recommendation Quality (AIRQ)	0.202	76.53	Very High
Social Competition (SC)	0.093	69.74	Low
Real-Time Feedback (RTF)	0.190	75.91	High
Flow Experience (FE)	0.768	80.67	Critical Priority

The Flow Experience is seen as the most important aspect as well as the one performed well in this case, with AI Recommendations Quality and Real-time Feedback ranking second in the Managers' Criticality Analysis.

Explainable Machine Learning (XGBoost with SHAP Analysis)

Table 14. XGBoost Model Performance

Performance Metric	Training Data	Testing Data
R ²	0.931	0.904
RMSE	0.214	0.248
MAE	0.167	0.191
MAPE (%)	5.42	6.18

Both the training and testing datasets show that the Predictive Power of the XGBoost Algorithm is outstanding, as it has both a high R-squared value and low error in the predictions.

7. Discussion

These sets of findings support the theoretical framework, which is related to S-O-R theory and the Law of Attraction and comes from prior research. It all connects. The main propositions H1 through H7, as well as their corresponding mediational hypotheses, H8a through H8f, also found great empirical support. This implies that AI-based virtual game components like artificial intelligent agents, an artificial reward system, scalable goals, user interpretation of recommendations, a competitive environment, and automatic responses do increase the sense of flow in customers, which in turn increases the commitment of consumers to the digital marketplace. Let us denote these dimensions as sets of linear relationships in which AI recommendation quality and real-time feedback had the most major impact on restoring the flow in the sense of the strongest one observed. Lastly and not least, the antecedent is a key ingredient of customer engagement strategy in relation to flow experience.

The uniqueness of this paper is that it combines several dimensions of AI-enabled gamification using a single integrated framework of SOR and Flow Theory and views several perspectives on the same problem, that is, the viewer flow as the centripetal force in consumer experience. Instead of focusing on the analysis using only one lens as earlier studies did, the present dissertation employs a combination of methods: PLS-SEM, NCA, and IPMA. Apart from that, the fact that the results were consistent across these techniques may increase the persuasiveness of the overall result, even when adjusting it to different focal areas. To be more precise, NCA flagged that flow experience was more of an essential build-up when providing instructions than other factors, while IPMA revealed what exactly the managers involved should give attention to. Thus, in sum, the study makes both theoretical and methodological improvements, stating the reasons as to how performance-based or engaging AI and gamification work for the benefit of one's consumer, if it does, and in this way, it adds to the details on how to develop intelligent, fully immersive, online trade systems.

8. Implications

The research can be considered a significant step forward in understanding the implications of gamification and AI innovation in the digital marketplace. Slated against the S-O-R model, Flow Theory states that the engagement potential of gamification comes from several sources, unevenly distributed amongst the six elements; AI personalization, intelligent rewards, adaptive challenges, AI recommendation usefulness, social competition aspects, and dynamic adjustments under the flow experience. It adds value to consumer behaviour and e-commerce research by explaining masterfully consumer engagement driven by AI-designed interactive experiences, as well as the main gist of that maintained attention. Additionally, the need to include explanatory PLS-SEM and necessity NCA, as well as prioritization of IPMA approaches, will both constitute methodological additions, which do not just aim at running through traditional single-method calculations, but also harbour more comprehensive paradigms operating in organizational leadership research.

The information provided is useful, and it allows practical conclusions that can help managers make informed decisions. This continuous emphasis (repeated identification in the results) on the flow experience, AI recommendations, and real-time feedback indicates that the resources of an organization should be aimed at the integration of smart recommendation systems, customized interactions, and instant feedback blocks that facilitate customer enjoyment. Thus, the study presents an innovative approach based on the research that enables this phenomenon in the settings understanding-digital commerce and presents issues of science or science of the business/others-will probably produce benefits for further improvement of that technique.

9. Conclusion

This particular study attempted to investigate how AI-enhanced gamification influences the engagement of consumers in e-commerce from the perspective of flow experience as an S-O-R internal mediator and beyond to Flow Theory. The findings, in general, have become clear by confirming that levels of AI personalization, smart rewards, difficulty levels, quality of AI recommendations, social competition, and provision of real-time incentives contribute toward higher flow levels. Respectively, all these measures help to expand educational insight. Over these years, consumer engagement has developed well. This is because of the flow factors in the model, and the effect of consumer engagement has been more powerful than optimistic expectations. The researchers achieve this by adopting a multi-method analytical approach: PLS-SEM along with NCA and IPMA. Finally, what was most constructive from this mixing of methodologies was the explicit convergence of all these perspectives: general explanation, crucial beauty, synergistic relationships, and what each signal predicts specific actions. In short, fitting advanced methods around a shared model assists in putting the argument across larger methodological boundaries. The results are anticipated to be beneficial for the investigators as well as for the decision-making crowd who desire to have intelligent and customizable electronic commerce systems that are more engaging in nature. It is anticipated that such platforms will support the follow-up forms of customer engagement and serve long-term relationships with clients, especially when the industry is slowly shifting towards an AI-based business strategy.

10. Limitations and Future Scope

The design structure of cross-sectional studies is the main limitation, as it does not enable any long-term causal relationships to be established. In such a case, instead of the cross-sectional design, what is highly recommended are the longitudinal studies. Another such limitation is that the current research focuses on the consumers who use digital commerce platforms in a specific geographic scope; hence, other countries or other sectors may not be similar. In that sense, prospective investigations ought to be predominantly cross-cultural and even cross-platform, to validate the enterprise model accordingly. One more thing: these authors could develop more recent findings in the form of the elements of trust in AI, perceived levels of transparency, existing levels of privacy exposure, and the aspect of fairness in the algorithms.

By adopting incremental or chain research, they are in a position to better understand the effects of AI-based gamification on the customer's experience in the market.

References

- Bilgihan, A., Nusair, K., Okumus, F., & Cobanoglu, C. (2015). Applying flow theory to booking experiences: An integrated model in an online service context. *Information & Management*, 52(6), 668-678.
- Brodie, R. J., Hollebeek, L. D., Jurić, B., & Ilić, A. (2011). Customer engagement: Conceptual domain, fundamental propositions, and implications for research. *Journal of service research*, 14(3), 252-271.
- Csikszentmihalyi, M. (2011). *Torrent flow the psychology of optimal experience definition*. Erfurt, Germany: University of Erfurt.
- Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the academy of marketing science*, 48(1), 24-42.
- Eroglu, S. A., Machleit, K. A., & Davis, L. M. (2001). Atmospheric qualities of online retailing: A conceptual model and implications. *Journal of Business research*, 54(2), 177-184.
- Hamari, J., Koivisto, J., & Sarsa, H. (2014, January). Does gamification work?--a literature review of empirical studies on gamification. In *2014 47th Hawaii international conference on system sciences* (pp. 3025-3034). Ieee.
- Hoffman, D. L., & Novak, T. P. (2009). Flow online: lessons learned and future prospects. *Journal of interactive marketing*, 23(1), 23-34.
- Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014). Consumer brand engagement in social media: Conceptualization, scale development and validation. *Journal of interactive marketing*, 28(2), 149-165.
- Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the academy of marketing science*, 49(1), 30-50.
- Koivisto, J., & Hamari, J. (2019). The rise of motivational information systems: A review of gamification research. *International journal of information management*, 45, 191-210.
- Kshetri, N., Hughes, L., louise Slade, E., Jeyaraj, A., kumar Kar, A., Koohang, A., ... & Wright, R. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, 102642.

- Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, 80(6), 69–96.
- Mehrabian, A., & Russell, J. A. (1974). *An Approach to Environmental Psychology*. MIT Press.
- Novak, T. P., Hoffman, D. L., & Yung, Y.-F. (2000). Measuring the customer experience in online environments: A structural modeling approach. *Marketing Science*, 19(1), 22–42.
- Pappas, I. O., & Woodside, A. G. (2021). Fuzzy-set Qualitative Comparative Analysis (fsQCA): Guidelines for research practice in Information Systems and marketing. *International Journal of Information Management*, 58, 102310.
- Ringle, C. M., Wende, S., & Becker, J.-M. (2023). *SmartPLS 4*. SmartPLS GmbH.
- Ryan, R. M., & Deci, E. L. (2020). *Intrinsic and Extrinsic Motivation from a Self-Determination Theory Perspective*. *Contemporary Educational Psychology*, 61, 101860.
- Verhoef, P. C., Kannan, P. K., & Inman, J. J. (2021). From multi-channel retailing to omnichannel customer experience. *Journal of Retailing*, 97(2), 174–181.
- Xi, N., & Hamari, J. (2020). Does gamification affect brand engagement and equity? A systematic review of the literature. *International Journal of Information Management*, 54, 102151.
- Xu, X., Buhalis, D., & Weber, J. (2022). Serious games and gamification in the digital customer journey: A review and future research agenda. *Tourism Management*, 91, 104527.
- <https://docs.google.com/document/d/1PURjFtm6ZngcccE8xFvE7i51cM4-uVay/edit?usp=sharing&oid=110903084146784736668&rtpof=true&sd=true>

