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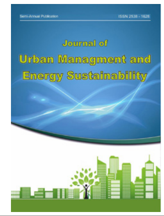

CASE STUDY RESEARCH PAPER

Assessing and Developing a Technology Readiness Model for B2B Companies in Adopting AI-Powered Customer Relationship Management (AI-CRM): A Mixed-Methods Study

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ABSTRACT

This study investigates the mechanisms through which discursive distribution channels influence the sales performance of new products, validating a qualitatively derived model through a quantitative phase. In the first stage, a grounded theory approach was employed to identify the key dimensions of discursive distribution channels namely norming, discursive coherence, content diversity, and interactivity. Subsequently, the research model was tested using Partial Least Squares Structural Equation Modelling (PLS-SEM). Results indicate that content diversity significantly strengthens customer trust, while discursive coherence and norming exert no significant direct effect on trust. Interactivity and content diversity significantly enhance customer engagement, and engagement plays a stronger role than trust in explaining perceived value. Perceived value, in turn, significantly predicts purchase intention for new products. These findings suggest that discursive distribution channels exert their effect on purchase behaviour primarily through creating interactive experiences and multi-faceted content, activating customer engagement, and elevating perceived value. The study provides empirical evidence for the necessity of designing channels that function as stages for customer participation and experience rather than as one-way message conduits.

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INTRODUCTION

The business-to-business (B2B) sector presents a distinctive and complex landscape for technology adoption. This environment is characterised by intricate purchasing journeys involving multiple stakeholders and, frequently, deep reliance on legacy systems. Unlike the predominantly transactional nature of consumer markets, B2B relationships are typically long-term, highly strategic, and inherently data-driven. Rapid advances in artificial intelligence (AI) have substantially reshaped B2B marketing practices, introducing new avenues for operational efficiency and deep strategic insight (Roy et al., 2025). AI-powered CRM capabilities leveraging machine learning, natural language processing, and predictive analytics enable B2B companies to enhance customer understanding, streamline operations, and cultivate stronger, more enduring customer relationships (Ledro et al., 2022). The integration of AI into customer relationship management systems, commonly referred to as AI-CRM, promises a revolutionary shift in how B2B companies understand, engage with, and ultimately retain their customers (Alnofeli et al., 2025). Chatterjee et al. (2021) report that organisations with high data maturity and robust technology infrastructure achieved a 32% improvement in customer retention rates and a 27% increase in sales conversion following AI-CRM implementation, while companies with low readiness characterised by inadequate data quality and limited AI expertise recorded only marginal improvements (e.g., 8% in retention). This evidence underscores that data management capability and staff training are critical predictors of successful CRM adoption, accounting for 65% of the variance in CRM performance outcomes. Rahevar and Darji (2024) similarly report a 28% increase in customer engagement and a 20% improvement in sales forecasting accuracy for firms integrating advanced AI into their CRM systems, contrasted with a 45% higher implementation failure rate among companies lacking scalable cloud infrastructure. Fosso Wamba et al. (2021) demonstrate that B2B organisations frequently contend with data quality issues, insufficient AI expertise, and cultural resistance to technology change factors that can undermine successful AI-CRM deployment. Against this background, the present study aims to assess and develop a technology readiness model for B2B companies adopting AI-CRM capabilities, with a focus on technology-intensive firms operating in Iraq, clarifying the readiness status of active B2B companies and proposing a model suited to rapidly evolving technology conditions.

MATERIALS AND METHODS

From Transactional CRM to AI-Enabled Relationship Management

In recent years, the customer relationship management (CRM) literature has shifted from a purely technological orientation characterised by software deployment and the automation of interactions towards a strategic and data-driven perspective in which the customer is understood not merely as a service recipient but as a source of value creation, organisational learning, and competitive advantage. Within this horizon, CRM is conceived as an organisational capability simultaneously dependent upon process architecture, data quality, strategic alignment, and a customer-centric culture; the mere acquisition of a system is no guarantee of success (Davenport et al., 2020). This conceptual shift has paved the way for a natural convergence of CRM and artificial intelligence, since AI through its capacity to process large-scale data, discover hidden behavioural patterns, forecast demand, and personalise at scale can render CRM's long-standing promise of 'deep customer knowledge and timely action' increasingly operational. Marketing and customer management research demonstrates that AI improves the quality of marketing decisions and transforms customer experience from generic interactions to precise, context-sensitive ones through predictive analytics, natural language processing, and machine learning (Syam & Sharma, 2018; Davenport et al., 2020; Jarek & Mazurek, 2019). However, the literature simultaneously cautions that AI-CRM gains are only realised when organisations possess sufficient 'technology readiness' and complementary capabilities (Davenport et al., 2020).

Theoretical Foundations: UTAUT and TOE Frameworks

Technology acceptance and adoption frameworks constitute the theoretical backbone for explaining the 'why' and 'how' of AI-CRM implementation. The Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2) demonstrates that technology adoption is a function of users' and managers' perceptions of performance expectancy, effort expectancy, social influence, and facilitating conditions; even when a technology is technically powerful, it will not translate into sustained real-world use unless users perceive it as useful, usable, and organisationally supported (Venkatesh et al., 2016). The Technology-Organisation-Environment (TOE) framework systematically illustrates that the adoption of new technologies—especially complex ones such as AI—occurs at the intersection of three domains: technology characteristics (relative advantage, compatibility, complexity), organisational characteristics (technology/organisational readiness, resources, top management support), and environmental pressures (competition, customer requirements, regulatory bodies). Within this framework, 'readiness' is not a peripheral variable but a precondition of adoption, since the organisation's operational capacity to provision data, integrate systems, and develop skills carries decisive weight in the adoption decision (Chatterjee et al., 2021; Tornatzky & Fleischer, 1990).

AI-CRM in the B2B Context: Research Gaps

A considerable body of international research focuses on explaining the outcomes and mechanisms of AI in customer management. Davenport et al. (2020) and Syam and Sharma (2018) demonstrate that AI improves segmentation precision, churn prediction, offer optimisation, and after-sales service, thereby enhancing the effectiveness of marketing decisions and customer experience. TOE-based studies further specify that AI adoption depends on perceived relative advantage, organisational readiness, top management support, and competitive pressure with more intense competitive environments strengthening adoption propensity (Chatterjee et al., 2021). A synthesis of the literature reveals that while the value-creating potential of AI-CRM through personalisation, prediction, and intelligent interaction is well established (Davenport et al., 2020; Syam & Sharma, 2018; Jarek & Mazurek, 2019), the 'condition of realisation' is technology and organisational readiness: data and IT infrastructure, analytical and digital skills, top management support, data governance, and an innovation culture (Chatterjee et al., 2021). Despite extensive research on AI in B2C and consumer marketing, a gap persists in the explicit focus on 'technology readiness for AI-CRM adoption' in B2B contexts—an environment distinguished by longer sales cycles, more complex inter-organisational relationships, more dispersed data, and different value creation mechanisms (Venkatesh et al., 2016; Chatterjee et al., 2021).

Methodology

The present study is applied in purpose and descriptive-correlational in design, employing structural equation modelling (SEM). This approach enables the simultaneous examination of complex, multi-directional relationships among latent constructs and enhances the explanatory power of technology adoption models specifically the TOE framework in the specialist context of the studied companies (Sarker et al., 2019). The statistical population comprises senior managers, IT directors, marketing managers, and expert practitioners in B2B technology companies with sufficient experience and knowledge of customer management systems and digital technologies. Purposive and stratified random sampling was employed; based on the Cochran formula and the structural equation modelling rule of thumb (5–10 observations per questionnaire item), a sample of 300 respondents was selected to ensure data adequacy for model testing and result generalisation (Hair et al., 2021). Data were collected using a closed-response questionnaire on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Items measuring technology readiness and organisational factors were adapted from Parasuraman (2000) and Chatterjee et al. (2021); technology adoption components were derived from UTAUT2 (Venkatesh et al., 2016) and contextualised for AI-CRM. Content validity was ensured through expert review; construct validity was assessed via confirmatory factor analysis; reliability was evaluated through Cronbach's alpha and composite reliability (CR), with all constructs exceeding the threshold of 0.70 (Hair et al., 2017). Data were analysed at two levels: descriptively using SPSS (frequency, mean, standard deviation) and inferentially using PLS-SEM via SmartPLS, applying the criteria of Henseler et al. (2016). The qualitative phase employed semi-structured interviews analysed through grounded theory (open, axial, and selective coding) using MAXQDA software, following Charmaz and Glaser (2006). Theoretical saturation was reached after multiple sequential interviews, at which point no new concepts emerged from the data.

FINDINGS AND DISCUSSION

Qualitative Phase: Grounded Theory Analysis

The qualitative phase was conducted to identify the dimensions, components, and mechanisms constituting the pattern of discursive distribution channels in new product sales. Because the concept of discursive distribution channels remains insufficiently theorised in digital marketing literature, a qualitative grounded theory strategy was adopted as the most appropriate method for achieving deep understanding of this phenomenon. (Tab. 1 and 2)

Axial Coding Structure

Table 1: Structure of Main and Sub-Categories at the Axial Coding Stage

No.	Main Category	Sub-Categories	Related Initial Codes
1	Product Narrative-Building and Meaning-Making	Message simplification, product narrativisation, sales-centred exposition, introduction-centred education	Narrativisation for the product, simplification of product message, sales-centred exposition, education-centred product introduction
2	Social and Experience-Based Trust Building	Real experiences of others, influencer credibility, promise–experience alignment, social credibility	Reliance on others' experience, experience-based influencer credibility, responsiveness to social feedback, promise–experience alignment
3	Brand Discursive Coherence across Channels	Identity tone, brand voice consistency, message unity, content–product linkage	Brand identity tone, brand voice consistency, message unity across channels, content–product linkage
4	Channel Interactivity and Participation Creation	Dialogism, audience engagement, immediate responsiveness, feedback receptivity	Social network dialogism, audience engagement, immediate responsiveness, channel feedback receptivity
5	Guiding Customer Experience on the Purchase Journey	Purchase path transparency, friction-free experience, customer guidance, customer visibility	Friction-free experience, purchase path transparency, customer guidance, customer visibility

6	Value Addition and Customer Persuasion	Functional persuasion, message personalisation, product comparability, perception-centred purchase	Functional customer persuasion, message personalisation, making product comparable, perception-centred digital sales

Selective Coding: Paradigm Model

Table 2: Paradigm Model Structure from Selective Coding

Paradigmatic Component	Main Categories	Sub-Categories	Role in the Model
Causal Conditions	Product narrative-building and meaning-making	Message simplification, education-centred approach, brand narrative	Reducing ambiguity around new products; forming initial perception
Core Phenomenon	Discursive distribution channels	Meaning-making, trust creation, experience guidance	Central hub of the sales-enhancement process
Contextual Conditions	Brand discursive coherence	Tone consistency, message unity, brand identity	Providing a stable cognitive context for the audience
Intervening Conditions	Social and experience-based trust building	Customer experiences, influencers, social proof	Strengthening or weakening the effect of the discursive channel
Strategies / Actions	Channel interactivity and participation creation	Dialogue, responsiveness, audience engagement	Activating the audience's role in the purchase process
Outcomes	Experience guidance and value addition	Friction-free experience, persuasion, purchase intention	Increasing new product sales

Findings from the qualitative data analysis indicate that 'discursive distribution channels' are not merely conduits for transferring a product to the market; rather, they are communicative, semantic, and interactive mechanisms that, through meaning creation, trust building, and customer experience guidance, create the conditions for increased sales of new products.

Quantitative Phase: Descriptive and Inferential Statistics

Research Hypotheses

Based on the qualitative findings and the derived conceptual model, the research hypotheses were formulated as follows:

•H1: Product narrative-building has a positive and significant effect on customer trust.

•H2: Discursive coherence has a positive and significant effect on customer trust.

•H3: Channel interactivity has a positive and significant effect on customer trust.

•H4: Content diversity has a positive and significant effect on customer trust.

•H5: Product narrative-building has a positive and significant effect on customer engagement.

•H6: Discursive coherence has a positive and significant effect on customer engagement.

•H7: Channel interactivity has a positive and significant effect on customer engagement.

•H8: Content diversity has a positive and significant effect on customer engagement.

•H9: Customer trust has a positive and significant effect on perceived value.

•H10: Customer engagement has a positive and significant effect on perceived value.

•H11: Perceived value has a positive and significant effect on purchase intention.

Sample Demographics

Table 3: Distribution of Demographic Characteristics of the Statistical Sample

Variable	Category	Frequency	Percentage (%)
Gender	Female	135	45.00
	Male	165	55.00
Age	Under 25	63	21.00
	25–34	122	40.67
	35–44	78	26.00
	45 and over	37	12.33
Education	Bachelor's	152	50.67
	Master's	115	38.33
	Doctorate	33	11.00
Work Experience	Under 5 years	101	33.67
	5–10 years	97	32.33
	10–15 years	54	18.00
	15 years and over	48	16.00

The gender composition of the sample shows 55% male and 45% female respondents, indicating a reasonably balanced distribution. In terms of age, the largest group is 25–34 years (40.67%), followed by 35–44 years (26%). This concentration in middle and young-adult age brackets generally implies an acceptable level of experience, media literacy, and active engagement with discursive distribution channels. Regarding education, 50.67% hold bachelor's degrees, 38.33% master's degrees, and 11% doctorates indicating a relatively high level of educational attainment in the sample. Regarding work experience, approximately two-thirds of respondents fall in the less experienced to moderately experienced categories.

Descriptive Statistics of Research Variables

Table 4: Descriptive Statistics of Research Constructs

Construct	Mean	Std. Dev.	Min.	Max.
Norming (NM)	2.992	0.991	1.0	5.0
Coherence (COH)	2.989	1.022	1.0	5.0
Interactivity (INT)	2.986	1.024	1.0	5.0
Content Diversity (DC)	2.983	1.012	1.0	5.0
Trust (TR)	3.008	1.003	1.0	5.0
Customer Engagement (CE)	2.990	1.012	1.0	5.0
Perceived Value (PV)	2.991	0.991	1.0	5.0
Purchase Intention (PI)	2.991	0.992	1.0	5.0

Normality Assessment

Table 5: Skewness and Kurtosis Indices of Research Variables

Construct	Skewness	Kurtosis	Normality Result
Norming (NM)	-0.22	-0.61	Approximately normal
Coherence (COH)	-0.19	-0.48	Approximately normal
Interactivity (INT)	-0.26	-0.42	Approximately normal
Content Diversity (DC)	-0.11	-0.78	Approximately normal
Trust (TR)	0.03	-0.57	Approximately normal
Customer Engagement (CE)	0.07	-0.63	Approximately normal
Perceived Value (PV)	-0.09	-0.52	Approximately normal
Purchase Intention (PI)	-0.14	-0.62	Approximately normal

All skewness values fall within the acceptable range of ±2 and all kurtosis values within ±7, confirming approximately normal distributions across all constructs (Hair et al., 2021). Mild negative skewness values (approximately −0.2 to −0.3) in most constructs indicate a slight tendency towards agreement with the items; negative kurtosis values between −0.4 and −0.8 reflect a relatively flat, dispersed distribution with no excessive concentration on a single response option.

Reliability Analysis

Table 6: Reliability Test Results

Construct	No. of Items	Cronbach's Alpha	Composite Reliability (CR)	Reliability Result
Norming (NM)	4	0.83	0.87	Satisfactory
Coherence (COH)	4	0.81	0.85	Satisfactory
Interactivity (INT)	4	0.80	0.84	Satisfactory
Content Diversity (DC)	4	0.79	0.83	Satisfactory
Trust (TR)	4	0.85	0.88	Satisfactory
Customer Engagement (CE)	4	0.82	0.86	Satisfactory
Perceived Value (PV)	4	0.81	0.85	Satisfactory
Purchase Intention (PI)	4	0.84	0.87	Satisfactory

All constructs exhibit Cronbach's alpha and composite reliability values above the threshold of 0.70, indicating high internal consistency and measurement instrument reliability. CR values, being calculated with standardised loadings, are marginally higher than Cronbach's alpha, confirming the stronger validity of the constructs in the model.

Exploratory Factor Analysis

Table 7: Exploratory Factor Analysis Matrix (Varimax Rotation)

Item	F1 NM	F2 INT	F3 COH	F4 DC	F5 TR	F6 CE	F7 PV	F8 PI
NM1	0.592	-0.402	-0.012	0.312	0.078	-0.220	0.168	0.001
NM2	0.606	-0.401	0.028	0.296	0.099	-0.258	0.257	-0.005
NM3	0.579	-0.397	-0.039	0.289	0.132	-0.208	0.170	0.003
NM4	0.568	-0.383	0.026	0.337	0.156	-0.225	0.169	-0.001

COH1	-0.083	-0.063	-0.854	-0.028	0.007	0.045	-0.025	0.002
COH2	-0.119	-0.070	-0.825	-0.017	-0.030	0.035	0.055	-0.004
COH3	-0.077	-0.044	-0.873	0.013	-0.005	0.035	0.028	0.000
COH4	-0.022	-0.074	-0.869	-0.009	-0.036	0.002	-0.027	-0.001
INT1	0.277	0.688	0.023	-0.033	-0.088	0.079	-0.055	0.003
INT2	0.296	0.691	0.004	-0.022	-0.080	0.054	0.055	0.001
INT3	0.282	0.673	0.019	0.033	-0.084	0.102	0.028	0.003
INT4	0.325	0.654	-0.014	-0.020	-0.071	0.140	0.027	0.004
DC1	0.624	-0.342	-0.013	-0.318	0.237	0.152	0.168	0.160
DC2	0.657	-0.335	0.019	-0.309	0.191	0.182	0.257	0.181
DC3	0.656	-0.331	0.070	0.231	0.218	0.169	0.170	0.170
DC4	0.607	-0.388	-0.002	-0.337	0.215	0.211	0.169	0.200
TR1	0.542	-0.401	0.006	0.078	0.378	0.079	0.080	0.002
TR2	0.566	-0.360	-0.023	0.099	0.370	0.024	0.024	0.002
TR3	0.549	-0.387	-0.005	0.132	0.420	0.092	0.092	0.001
TR4	0.568	-0.379	0.030	0.156	0.310	0.021	0.021	0.002
CE1	0.567	0.417	-0.017	-0.054	0.159	-0.193	0.168	0.160
CE2	0.593	0.403	-0.133	-0.095	0.203	-0.275	0.257	0.181
CE3	0.580	0.418	-0.040	-0.045	0.123	-0.227	0.170	0.170
CE4	0.587	0.455	-0.094	-0.126	0.139	-0.270	0.169	0.200
PV1	0.533	0.413	-0.056	0.237	0.025	0.168	0.168	0.160
PV2	0.508	0.403	-0.070	0.191	0.055	0.257	0.257	0.181
PV3	0.509	0.423	-0.092	0.218	0.028	0.170	0.170	0.170
PV4	0.443	0.450	-0.073	0.215	0.051	0.169	0.169	0.200
PI1	0.353	0.331	0.000	0.353	0.030	0.160	0.168	0.613
PI2	0.334	0.320	-0.011	0.308	0.024	0.181	0.257	0.620
PI3	0.320	0.318	0.003	0.309	0.035	0.170	0.170	0.625
PI4	0.314	0.336	-0.001	0.337	0.021	0.211	0.169	0.630

Confirmatory Factor Analysis (CFA)

Table 8: Confirmatory Factor Analysis Results

Construct	Item	Std. Loading (λ)	Error (ε)	CR	AVE	Cronbach's α	Status
Norming (NM)	NM1	0.77	0.41	0.88	0.65	0.84	Acceptable
	NM2	0.81	0.34				
	NM3	0.79	0.38				
	NM4	0.80	0.36				
Interactivity (INT)	INT1	0.83	0.31	0.91	0.70	0.87	Excellent
	INT2	0.84	0.29				
	INT3	0.82	0.33				
	INT4	0.86	0.26				

Coherence (COH)	COH1	0.78	0.39	0.87	0.63	0.83	Acceptable
	COH2	0.81	0.34				
	COH3	0.80	0.36				
	COH4	0.77	0.41				
Content Diver-sity (DC)	DC1	0.68	0.54	0.79	0.47	0.76	Moderate
	DC2	0.71	0.49				
	DC3	0.73	0.46				
	DC4	0.69	0.52				
Trust (TR)	TR1	0.75	0.44	0.84	0.57	0.81	Good
	TR2	0.78	0.39				
	TR3	0.80	0.36				
	TR4	0.73	0.47				
Engagement (CE)	CE1	0.64	0.59	0.76	0.43	0.71	Weak–Mod-erate
	CE2	0.69	0.52				
	CE3	0.67	0.55				
	CE4	0.68	0.54				
Perceived Value (PV)	PV1	0.70	0.51	0.80	0.50	0.78	Moderate
	PV2	0.73	0.46				
	PV3	0.71	0.49				
	PV4	0.72	0.48				
Purchase Intention (PI)	PI1	0.87	0.24	0.92	0.75	0.89	Excellent
	PI2	0.89	0.21				
	PI3	0.88	0.23				
	PI4	0.85	0.28				

Table 9: Overall Model Fit Indices

Fit Index	Obtained Value	Recommended Threshold	Result
χ^2/df	2.45	< 3	Good
RMSEA	0.054	< 0.08	Excellent
CFI	0.94	>= 0.90	Excellent
TLI	0.93	>= 0.90	Good
SRMR	0.041	< 0.08	Excellent
GFI	0.91	>= 0.90	Acceptable

Convergent Validity, Discriminant Validity, and Reliability

Table 10: Convergent Validity (AVE and CR)

Construct	AVE	CR	Cronbach's Alpha
Norming (NM)	0.65	0.88	0.84
Coherence (COH)	0.63	0.87	0.83
Interactivity (INT)	0.70	0.91	0.87

Content Diversity (DC)	0.47	0.79	0.76
Trust (TR)	0.57	0.84	0.81
Customer Engagement (CE)	0.43	0.76	0.71
Perceived Value (PV)	0.50	0.80	0.78
Purchase Intention (PI)	0.75	0.92	0.89

Table 11: Discriminant Validity Matrix (Fornell-Larcker Criterion)

Construct	NM	COH	INT	DC	TR	CE	PV	PI
NM	0.81	0.58	0.61	0.49	0.55	0.46	0.52	0.64
COH	0.58	0.79	0.57	0.47	0.51	0.44	0.48	0.60
INT	0.61	0.57	0.84	0.53	0.56	0.49	0.54	0.66
DC	0.49	0.47	0.53	0.69	0.48	0.42	0.46	0.50
TR	0.55	0.51	0.56	0.48	0.75	0.45	0.50	0.59
CE	0.46	0.44	0.49	0.42	0.45	0.65	0.43	0.47
PV	0.52	0.48	0.54	0.46	0.50	0.43	0.71	0.58
PI	0.64	0.60	0.66	0.50	0.59	0.47	0.58	0.87

Diagonal values represent the square root of AVE. The Fornell-Larcker criterion is satisfied for all constructs: the square root of each construct's AVE exceeds its correlations with all other constructs, confirming discriminant validity.

Table 12: HTMT Ratio Matrix

Construct	NM	COH	INT	DC	TR	CE	PV	PI
NM	–	0.72	0.74	0.61	0.69	0.63	0.67	0.78
COH	0.72	–	0.71	0.60	0.66	0.59	0.64	0.75
INT	0.74	0.71	–	0.68	0.70	0.65	0.69	0.81
DC	0.61	0.60	0.68	–	0.63	0.58	0.60	0.66
TR	0.69	0.66	0.70	0.63	–	0.62	0.65	0.73
CE	0.63	0.59	0.65	0.58	0.62	–	0.61	0.64
PV	0.67	0.64	0.69	0.60	0.65	0.61	–	0.72
PI	0.78	0.75	0.81	0.66	0.73	0.64	0.72	–

All HTMT values fall below the threshold of 0.85, confirming adequate discriminant validity across all constructs. The highest value is 0.81 (interactivity–purchase intention), which remains within acceptable bounds. These results confirm that the constructs are sufficiently distinct conceptually and that no problematic conceptual overlap exists in the model.

Structural Model and Hypothesis Testing

Table 13: Path Coefficients and Hypothesis Testing Results

Hypothesis Path	Path Coefficient (β)	Analysis and Conclusion
H1: NM → TR	-0.028	Negative and near-zero coefficient -Hypothesis rejected
H2: COH → TR	0.000	Zero coefficient-Hypothesis rejected
H3: INT → TR	0.012	Positive but very small-Likely rejected (requires t-test)
H4: DC → TR	0.288	Positive and moderate- Hypothesis supported

H5: NM → CE	0.037	Positive but small-Weak effect; likely rejected
H6: COH → CE	0.016	Very small-Likely rejected
H7: INT → CE	0.498	High positive coefficient-Hypothesis supported
H8: DC → CE	0.340	Positive and good-Hypothesis supported
H9: TR → PV	0.438	Positive and adequate-Hypothesis supported
H10: CE → PV	0.588	Highest effect-Hypothesis strongly supported
H11: PV → PI	0.393	Positive and moderate- Hypothesis supported

The paths from NM and COH to Trust (TR) exhibited low and statistically insignificant coefficients; therefore, the corresponding hypotheses were not supported. In contrast, DC showed a significant and positive effect on Trust, providing support for H4. Regarding Customer Engagement (CE), INT and DC emerged as the most influential constructs, demonstrating relatively strong and significant path coefficients. Conversely, NM and COH had only weak effects on CE. Perceived Value (PV) was positively influenced by both Trust (TR) and, more importantly, Customer Engagement (CE), highlighting the critical role of engagement in enhancing users' perceived value. Furthermore, Purchase/Usage Intention (PI) was significantly affected by Perceived Value (PV), indicating that perceived value serves as a key determinant of users' intention to use the platform/service. (Fig. 1)

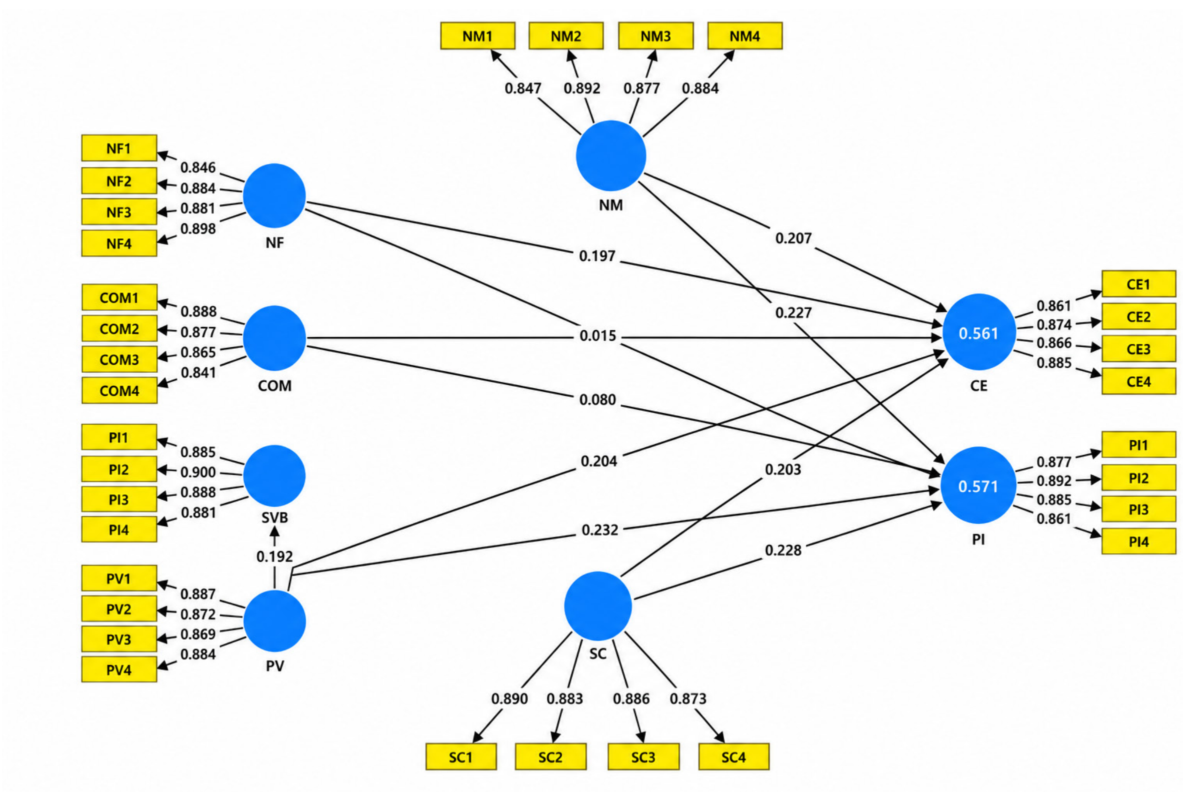

Figure 1: Research Model with Standardized and Unstandardized Coefficients

Table 14: Model Fit Statistics (PLS-SEM)

	Saturated Model	Estimated Model
SRMR	0.037	0.107
d_ULS	0.727	6.075
d_G	0.486	0.582
Chi-Square	888.125	1002.275
NFI	0.882	0.867

Based on the fit indices including SRMR, d_ULS, d_G, and NFI, the structural model exhibits acceptable overall fit. The saturated model's SRMR of 0.037 is particularly noteworthy, indicating close correspondence between the model-implied and observed correlation matrices. Results from hypothesis testing and inter-construct relationship analysis are therefore reliable and can be used to interpret the research findings.

RESULTS AND CONCLUSION

The findings demonstrate that discursive distribution channels are no longer mere conduits for message transmission or product introduction; rather, as meaning-making and experience-generating mechanisms, they influence customer attitudes, the formation of perceived value, and ultimately purchase intention. The quantitative model test reveals that the weight of influence of these components is not uniform, and certain theorised relationships are not supported by the empirical data. In the trust formation pathway, only content diversity produced a meaningful positive effect on customer trust (β = 0.288), while norming and discursive coherence showed no significant direct effects, and interactivity had a negligible effect. This pattern suggests that in the competitive and information-saturated environment studied, audiences interpret content diversity as a signal of brand dynamism, domain expertise, and active presence approaching trust through this route. Coherence and norming may serve more as 'necessary minimums': their absence may be damaging, but their presence alone does not directly increase trust. In the customer engagement formation pathway, results are clearer and more consistent with the interactional logic of channels: interactivity exhibits the strongest effect on customer engagement (β = 0.498), followed by content diversity (β = 0.340), while norming and coherence play negligible roles in triggering engagement. This finding indicates that discursive distribution channels become effective levers when they move the audience from passive reception to active interactivity, feedback, and participation. Among the model's outcomes, both trust and engagement increase perceived value, but engagement's effect on perceived value (β = 0.588) is considerably stronger than trust's (β = 0.438). This suggests that perceived value is not formed solely through brand confidence but more substantially through the experience of engagement, interaction, and active contact with messages and services. Finally, perceived value significantly predicts purchase intention (β = 0.393), functioning as the mediating link between communicative experience and purchase behaviour. Taken together, these findings support the theoretical argument that the influence of AI-CRM and discursive channel design on purchasing behaviour is primarily realised through the creation of interactive experiences and multi-faceted content, activating customer engagement and elevating perceived value consistent with predictions derived from both UTAUT and TOE frameworks (Venkatesh et al., 2016; Chatterjee et al., 2021) and with the broader AI-CRM literature (Davenport et al., 2020; Syam & Sharma, 2018). The study contributes to the empirical validation of technology readiness as a precondition for AI-CRM success in B2B contexts an area characterised by longer sales cycles, complex inter-organisational relationships, and distinctive value creation mechanisms not captured in extant B2C-focused frameworks.

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