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Enhancing Digital Retail Through Extended Reality: Consumer Experience and Behavioral Effects

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Abstract
The rapid evolution of digital retail has intensified the need for immersive technologies that enhance consumer engagement and reduce the limitations of conventional online shopping. Extended reality (XR), encompassing virtual, augmented, and mixed reality, has emerged as a promising solution by enabling interactive, experiential, and realistic shopping environments. This study investigates the influence of extended reality on consumer experience, shopping behavior, and behavioral outcomes in digital retail contexts. A quantitative research design was adopted, and primary data were collected from 174 respondents using a structured questionnaire. The study employed exploratory factor analysis, confirmatory factor analysis, and structural equation modeling to examine the relationships among key constructs, including customer experience, customer behaviour, shopping behaviour, extended reality, and behavioural outcomes. The findings reveal that customer behaviour significantly influences both customer experience and shopping behaviour, while customer experience positively affects shopping behaviour. However, the direct effects of extended reality on behavioural outcomes were found to be insignificant, indicating that XR primarily operates through experiential and behavioural mechanisms rather than direct influence. Model fit indices confirmed the adequacy and robustness of the proposed research model. The results highlight the importance of factors such as trust, emotional connection, immersive enjoyment, and convenience in shaping consumer responses within XR-enabled retail environments. Overall, the study contributes to the growing body of literature on immersive retailing by providing empirical evidence on the pathways through which extended reality shapes consumer decision-making. The findings offer valuable insights for retailers and technology developers seeking to leverage XR strategically to enhance customer experience, foster engagement, and improve long-term consumer outcomes in digital retail environments.

Keywords: Extended Reality, Digital Retail, Consumer Experience, Shopping Behaviour, Behavioural Outcomes

1. Introduction
The rapid advancement of digital technologies has significantly transformed the retail landscape, with extended reality (XR) emerging as a powerful tool for enhancing online shopping experiences. XR, encompassing virtual reality, augmented reality, and mixed reality, enables consumers to interact with products in immersive and realistic ways that closely resemble physical store environments (Martin, 2020). By integrating features such as three-dimensional product visualization, virtual assistance, and real-time customization, XR addresses key limitations of traditional e-commerce, including lack of tangibility, limited engagement, and uncertainty in purchase decisions. As consumers increasingly seek

convenient, interactive, and trustworthy digital shopping experiences, understanding how XR influences customer experience and behavior has become a critical area of academic and managerial interest (Huang, 2020).

Despite growing adoption, the effectiveness of XR in driving favorable consumer outcomes remains underexplored, particularly in relation to behavioral mechanisms and experiential factors. Variables such as data security, purchase trust, emotional connection, shopping convenience, and immersive enjoyment play a crucial role in shaping how consumers perceive and respond to XR-enabled retail environments (Flavian, 2020). Moreover, customer behaviors, shopping patterns, and behavioral outcomes—such as revisit intention, decision speed, purchase satisfaction, and habit formation—are influenced by the extent to which XR successfully replicates the in-store experience and fosters engagement. Therefore, this study aims to examine the influence of extended reality on consumer experience, shopping behavior, and behavioral outcomes in digital retail environments, providing empirical insights into the pathways through which immersive technologies shape contemporary consumer decision-making (Jessen, 2020).

2. Review Of Literature

The growing adoption of extended reality in digital retail has heightened scholarly attention toward customer experience dimensions, particularly data security, purchase trust, emotional connection, and shopping convenience (Martin, 2020). Prior studies emphasize that perceived data security is a foundational element in technology-mediated shopping, as concerns regarding personal and financial information significantly influence consumers' willingness to engage with immersive platforms. Secure XR environments enhance purchase trust by reducing uncertainty and increasing confidence in transactions (Hudson, 2020). Furthermore, XR technologies facilitate emotional connections by enabling interactive and immersive brand experiences, allowing consumers to feel psychologically closer to products and brands (Hajli, 2020). Shopping convenience is also enhanced through XR features such as real-time visualization and seamless navigation, which reduce cognitive effort and improve overall shopping efficiency compared to conventional online retail formats (Flavian, 2021).

Research on customer behavioral responses in digital retail highlights the importance of revisit intention, risk concern, preference change, and decision speed (Childers, 2021). Studies suggest that engaging XR experiences positively influence revisit intention, as consumers are more likely to return to platforms that offer immersive and enjoyable interactions (Kim, 2020). However, risk concern remains a critical factor, particularly related to system glitches, usability issues, and privacy risks, which may inhibit repeated usage. XR exposure has been shown to alter consumer preferences by allowing realistic product evaluation, leading to shifts in brand or product choices (Marín-García, 2020). Additionally, decision speed is often accelerated in XR-enabled environments, as enhanced visualization and interaction reduce ambiguity and facilitate quicker purchase decisions (Hilken, 2022).

Within the context of shopping behavior, scholars have examined description reliance, customization enjoyment, immersive fun, and purchase hesitation (Park, 2021). XR shopping reduces consumers' reliance on textual descriptions and third-party reviews by providing experiential product information through 3D visualization and simulations (Blut, 2021). Customization enjoyment emerges as a key driver of engagement, as consumers value the ability to personalize products in real time (Jessen, 2020). The immersive and playful nature of XR contributes to perceived fun, which positively affects user engagement and time spent on platforms. Moreover, XR has been found to reduce purchase hesitation by increasing product clarity and confidence, thereby minimizing perceived risk associated with online purchases (ang, 2022).

Studies focusing on behavioral outcomes identify brand trial, product credibility, purchase satisfaction, and habit influence as critical consequences of XR adoption. XR experiences encourage brand trial by lowering the perceived risk of trying unfamiliar brands through realistic product interaction (Huang, 2021). Product credibility is enhanced when consumers perceive XR as a reliable and transparent technology that accurately represents product attributes. Higher purchase satisfaction is consistently linked to immersive and interactive shopping experiences, as expectations are more closely aligned with actual product performance (Pantano, 2020). Over time, repeated exposure to XR shopping can influence habitual behavior, gradually shaping consumers' long-term shopping patterns and platform preferences (Rauschnabel, 2022).

Finally, literature on extended reality features underscores the roles of in-store feel, store preference, social engagement, and virtual assistance in transforming digital retail. XR technologies replicate the in-store feel by simulating physical environments, thereby bridging the gap between online and offline shopping (McLean, 2021). This enhanced realism often leads to a stronger preference for XR-based stores over traditional e-commerce platforms. Social engagement is also amplified, as immersive experiences motivate consumers to share interactions and brand content on social media (Verhagen, 2021). Additionally, virtual assistance through AI-driven avatars or sales assistants improves information accessibility and customer support, contributing to a more interactive and responsive shopping experience (Papagiannidis, 2021). Collectively, these elements position extended reality as a transformative force in shaping consumer experience, behavior, and outcomes in digital retail environments (Limayam, 2021).

3. Methodological Framework

3.1. Statement of the Problem

The rapid growth of digital retail has transformed the way consumers search for information, evaluate products, and make purchase decisions. While traditional e-commerce platforms offer convenience and accessibility, they often lack experiential elements such as physical interaction, real-time product evaluation, and personalized assistance, which can lead to uncertainty, low trust, and purchase hesitation among consumers. To address these limitations, retailers are increasingly adopting extended reality (XR) technologies to create immersive, interactive, and engaging shopping environments. However, despite the increasing implementation of XR in digital retail, there is limited empirical evidence explaining how these technologies influence consumer experience, shopping behavior, and subsequent behavioral outcomes.

Existing studies on XR in retail primarily focus on technological adoption or user attitudes, with insufficient attention given to the interconnected roles of customer experience, customer behavior, and shopping behavior in shaping final behavioral outcomes such as purchase satisfaction, revisit intention, and habit formation. Moreover, concerns related to data security, perceived risk, and usability challenges may moderate or hinder the effectiveness of

XR-enabled shopping environments. The lack of comprehensive, integrative models examining these relationships creates a research gap in understanding the true value of XR in digital retail contexts. Therefore, this study seeks to address this gap by systematically investigating the influence of extended reality on consumer experience, shopping behavior, and behavioral outcomes, providing empirical insights that can guide both academic research and managerial decision-making in immersive digital retail environments.

3.2. Objectives

- To examine the influence of extended reality on consumer experience and shopping behavior in digital retail environments.
- To analyze the impact of extended reality–enabled shopping on consumer behavioral outcomes, including purchase satisfaction, revisit intention, and habit formation.

3.3. Research Design

The study adopts a quantitative research design using a descriptive and explanatory approach to examine the influence of extended reality on consumer experience, shopping behavior, and behavioral outcomes in digital retail environments. A cross-sectional survey design was employed to collect primary data from respondents who have prior experience with online shopping and exposure to XR-enabled retail platforms.

3.4. Population and Sample

The target population comprises digital retail consumers familiar with online shopping technologies. A sample of 174 respondents was selected using a convenience sampling technique, which is appropriate for exploratory and technology-adoption studies. The sample size satisfies the minimum requirements for factor analysis and structural equation modeling, as supported by KMO and Hoelter indices.

3.5. Data Collection Instrument

Data were collected using a structured questionnaire consisting of three sections: socio-demographic information, perceived benefits and behaviors related to XR shopping, and behavioral outcomes. Measurement items were adapted from prior validated studies and modified to suit the XR retail context. Responses were recorded using a five-point Likert scale, ranging from strongly disagree to strongly agree.

3.6. Variables and Measures

The study includes Extended Reality as the independent variable; Customer Experience, Customer Behaviour, and Shopping Behaviour as mediating variables; and Behavioural Outcome as the dependent variable. Constructs were measured using multiple observed indicators, including data security, purchase trust, immersive fun, customization enjoyment, purchase satisfaction, and habit influence.

3.7. Data Analysis Techniques

Data analysis was conducted using SPSS and AMOS. Descriptive statistics were used to analyze demographic characteristics. Exploratory Factor Analysis (EFA) with Maximum Likelihood extraction and Varimax rotation was performed to assess construct validity. KMO and Bartlett's Test confirmed sampling adequacy and factorability. Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were employed to test the hypothesized relationships. Model fit was evaluated using multiple indices, including CMIN/DF, CFI, TLI, IFI, RMSEA, and PCLOSE.

3.8. Reliability and Validity

Reliability was assessed using Cronbach's alpha and composite reliability measures to ensure internal consistency. Convergent and discriminant validity were established through factor loadings, average variance extracted, and model fit indices.

3.9. Ethical Considerations

Participation was voluntary, and respondents were informed about the purpose of the study. Confidentiality and anonymity were ensured, and data were used solely for academic research purposes.

4. Data Analysis On Extended Reality Outcomes

4.1. The socio-demographic profile of the respondents

The socio-demographic profile of the respondents shows that the majority belonged to the younger and economically active age groups. Approximately 68 respondents (39%) were aged 18–25, followed by 52 respondents (30%) in the 26–35 age group. About 28 respondents (16%) were aged 36–45, while 17 respondents (10%) fell within the 46–55 category, and the remaining 9 respondents (5%) were 56 years and above. In terms of gender, around 92 respondents (53%) were male, and 82 respondents (47%) were female, indicating a relatively balanced gender distribution. Regarding education, most respondents were undergraduates (71 respondents; 41%), followed by postgraduates (46 respondents; 26%), diploma holders (27 respondents; 16%), high school graduates (19 respondents; 11%), and a smaller group of doctorate holders (11 respondents; 6%). With respect to employment status, approximately 58 respondents (33%) were students, 64 respondents (37%) were employed, 29 respondents (17%) were self-employed, 15 respondents (9%) were unemployed, and 8 respondents (4%) were retired. In terms of monthly income, around 49 respondents (28%) earned below INR 25,000, 44 respondents (25%) earned between INR 25,000–50,000, 38 respondents (22%) fell in the INR 50,001–1,00,000 category, 27 respondents (16%) earned INR 1,00,001–1,50,000, and 16 respondents (9%) earned above INR 1,50,000. Additionally, 101 respondents (58%) were single, while 73 respondents (42%) were married.

With regard to online shopping behavior and technology-related characteristics, approximately 61 respondents (35%) reported shopping online weekly, 47 respondents (27%) shopped monthly, 28 respondents (16%) shopped seasonally, 23 respondents (13%) shopped occasionally, and 15 respondents (9%) shopped rarely. In terms of device usage, the majority used smartphones (89 respondents; 51%), followed by laptops or desktops (46 respondents; 26%), tablets (21 respondents; 12%), VR/AR devices (12 respondents; 7%), and other devices (6 respondents; 4%). Social media was found to have a noticeable influence on purchase decisions, with 39 respondents (22%) being strongly influenced, 54 respondents (31%) influenced, 41 respondents (24%) neutral, 27 respondents (16%) less influenced, and 13 respondents (7%) not influenced. Regarding comfort with technology adoption, approximately 48 respondents (28%) reported being very comfortable, 57 respondents (33%) comfortable, 36 respondents (21%) neutral, 21 respondents (12%) uncomfortable, and 12 respondents (6%) very uncomfortable, indicating an overall positive inclination toward adopting XR-enabled shopping technologies.

4.2. Factor Analysis on Extended Reality Outcomes

The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy yielded a value of 0.705, indicating an acceptable level of shared variance among the variables and confirming that the sample is suitable for factor analysis. In addition, Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 1014.429$, df = 190, p = .000), demonstrating that the correlation matrix is not an identity matrix and that sufficient intercorrelations exist among the variables. Together, these results confirm the appropriateness of the data for factor analysis and support the validity of subsequent multivariate analyses.

Table 1: Communalities on Extended Reality Outcomes

Variables	Initial	Extraction
Data Security	.286	.338
Purchase Trust	.336	.383
Emotional Connection	.461	.630
Shopping Convenience	.372	.418
Revisit Intention	.284	.255
Risk Concern	.264	.237
Preference Change	.280	.313
Decision Speed	.397	.579
Description Reliance	.400	.470
Customization Enjoyment	.441	.476
Immersive Fun	.416	.514
Purchase Hesitation	.475	.477
Brand Trial	.269	.182
Product Credibility	.382	.374
Purchase Satisfaction	.535	.678
Habit Influence	.493	.580
In-Store Feel	.471	.542
Store Preference	.615	.773
Social Engagement	.345	.367
Virtual Assistance	.538	.589
Extraction Method: Maximum Likelihood.		

Table 2. Total Variance Explained on Extended Reality Outcomes

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.585	17.923	17.923	2.822	14.112	14.112	2.240	11.198	11.198
2	2.569	12.846	30.769	2.365	11.827	25.939	1.896	9.482	20.680
3	2.305	11.525	42.293	1.826	9.131	35.070	1.811	9.054	29.734
4	1.732	8.662	50.956	1.183	5.916	40.987	1.785	8.925	38.659
5	1.571	7.855	58.811	.977	4.887	45.873	1.443	7.215	45.873
6	.935	4.673	63.484						
7	.888	4.441	67.926						

8	.822	4.109	72.034						
9	.708	3.541	75.576						
10	.671	3.357	78.932						
11	.605	3.027	81.960						
12	.562	2.809	84.768						
13	.525	2.624	87.392						
14	.477	2.384	89.777						
15	.435	2.177	91.954						
16	.403	2.014	93.968						
17	.369	1.847	95.815						
18	.336	1.678	97.493						
19	.260	1.298	98.790						
20	.242	1.210	100.000						
Extraction Method: Maximum Likelihood.									

The results of the Total Variance Explained indicate that, using the Maximum Likelihood extraction method, five factors were retained based on eigenvalues greater than 1. The initial eigenvalues show that Factor 1 explained 17.923% of the variance, followed by Factor 2 (12.846%), Factor 3 (11.525%), Factor 4 (8.662%), and Factor 5 (7.855%), cumulatively accounting for 58.811% of the total variance. After extraction, these five factors jointly explained 45.873% of the variance, with Factor 1 contributing 14.112%, Factor 2 11.827%, Factor 3 9.131%, Factor 4 5.916%, and Factor 5 4.887%. Following rotation, the variance was more evenly distributed across the factors, with Factor 1 explaining 11.198%, Factor 2 9.482%, Factor 3 9.054%, Factor 4 8.925%, and Factor 5 7.215%, while maintaining the same cumulative variance of 45.873%. These results suggest a stable and interpretable factor structure, with the retained factors adequately capturing the underlying dimensions of the dataset.

Table 3. Rotated Factor Matrix[a] on Extended Reality Outcomes

	Factor				
	1	2	3	4	5
Data Security	-.139	.045	.560	.031	-.045
Purchase Trust	.030	-.015	.574	-.016	.228
Emotional Connection	-.009	.165	.752	.107	.160
Shopping Convenience	-.065	.224	.580	-.102	.128
Revisit Intention	-.029	-.001	.036	-.105	.492
Risk Concern	-.164	.049	.133	.052	.433
Preference Change	-.091	.192	.081	.065	.507
Decision Speed	.114	.172	.118	-.014	.723
Description Reliance	.056	.681	-.029	.034	.035
Customization Enjoyment	.071	.644	.139	-.067	.181
Immersive Fun	-.073	.703	.094	-.064	.043
Purchase Hesitation	-.098	.587	.256	.123	.206
Brand Trial	-.040	.055	-.090	.411	.023
Product Credibility	.033	.061	-.034	.602	.076
Purchase Satisfaction	-.007	-.135	.045	.807	-.080

Habit Influence	-.008	-.058	.208	.724	-.101
In-Store Feel	.716	-.015	.023	-.034	-.166
Store Preference	.860	-.046	-.168	-.015	-.057
Social Engagement	.597	.013	.071	-.057	-.045
Virtual Assistance	.730	.022	-.207	.094	.068
Extraction Method: Maximum Likelihood. Rotation Method: Varimax with Kaiser Normalization.					
a. Rotation converged in 5 iterations.					

The rotated factor matrix obtained using Maximum Likelihood extraction with Varimax rotation reveals a clear and interpretable five-factor structure, with items loading strongly on their respective constructs and minimal cross-loadings. Factor 1 is characterized by high loadings on In-Store Feel (.716), Store Preference (.860), Social Engagement (.597), and Virtual Assistance (.730), representing the Extended Reality dimension. Factor 2 shows strong loadings for Description Reliance (.681), Customization Enjoyment (.644), Immersive Fun (.703), and Purchase Hesitation (.587), indicating the Shopping Behaviour construct. Factor 3 is defined by Data Security (.560), Purchase Trust (.574), Emotional Connection (.752), and Shopping Convenience (.580), reflecting the Customer Experience dimension. Factor 4 includes Brand Trial (.411), Product Credibility (.602), Purchase Satisfaction (.807), and Habit Influence (.724), representing Behavioural Outcomes. Factor 5 is associated with Revisit Intention (.492), Risk Concern (.433), Preference Change (.507), and Decision Speed (.723), capturing Customer Behaviour. Overall, the rotated solution demonstrates strong factor loadings above the acceptable threshold, confirms construct validity, and supports the theoretical structure of extended reality influences on consumer experience, shopping behaviour, and behavioural outcomes in digital retail environments.

4.3. Extended Reality: Consumer Experience and Behavioral Effects Model

Structural Equation Modeling (SEM) was employed to examine the complex relationships among extended reality, customer experience, customer behaviour, shopping behaviour, and behavioural outcomes in digital retail environments. SEM enables the simultaneous assessment of both measurement and structural models, allowing for a comprehensive evaluation of latent constructs and their interrelationships. This approach provides robust insights into the direct and indirect effects within the proposed research framework.

4.3.1 Research Hypotheses

H1: Customer behaviour has a significant positive effect on customer experience in extended reality–enabled digital retail environments.
H2: Customer behaviour has a significant positive effect on shopping behaviour in extended reality–based shopping contexts.
H3: Customer experience has a significant positive effect on shopping behaviour in digital retail environments.
H4: Customer experience has a significant effect on extended reality usage in digital retail environments.
H5: Shopping behaviour has a significant effect on extended reality usage in digital retail environments.
H6: Customer experience has a significant positive effect on behavioural outcomes in extended reality–enabled digital retail environments.

H7: Extended reality has a significant positive effect on behavioural outcomes in digital retail environments.

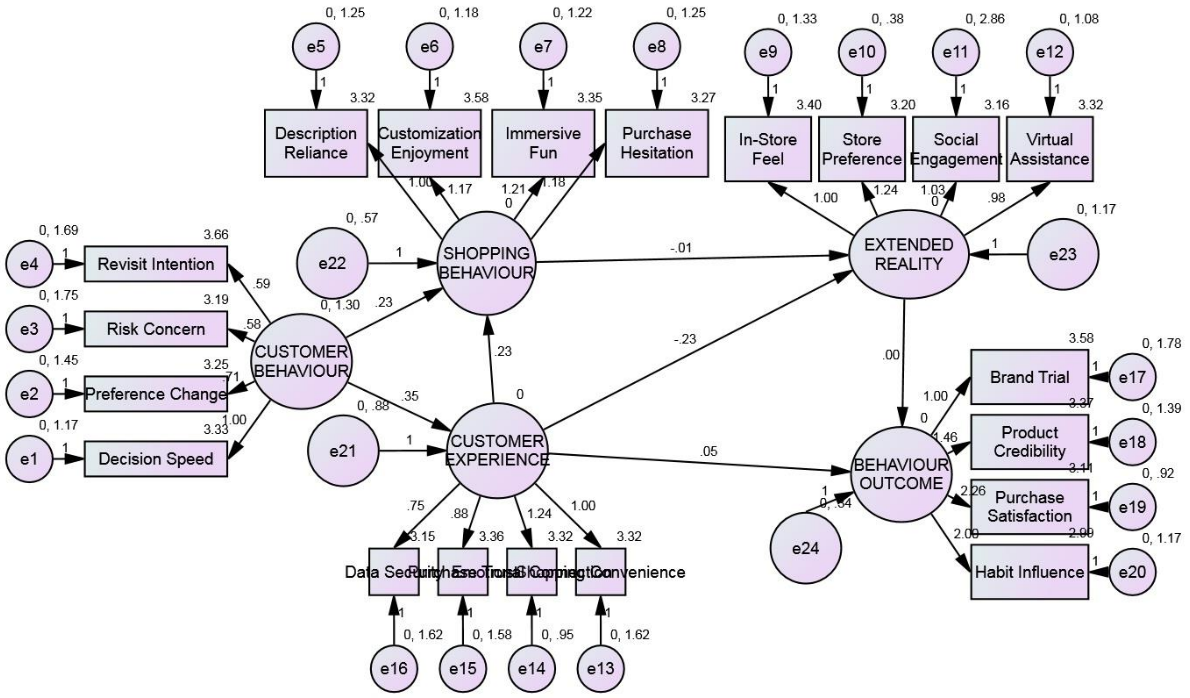

Fig. 1 Extended Reality: Consumer Experience and Behavioral Effects Model

Table 4. Path analysis results of Extended Reality: Consumer Experience and Behavioral Effects Model

Path Hypothesis			Estimate	Estimate	S.E.	C.R.	P
Customer Experience	<---	Customer Behaviour	.394	.352	.108	3.270	.001
Shopping Behaviour	<---	Customer Behaviour	.306	.232	.094	2.476	.013
Shopping Behaviour	<---	Customer Experience	.277	.235	.097	2.416	.016
Extended Reality	<---	Customer Experience	-.212	-.229	.117	-1.959	.050
Extended Reality	<---	Shopping Behaviour	-.007	-.008	.133	-.063	.950
Behaviour Outcome	<---	Customer Experience	.087	.050	.059	.856	.392
Behaviour Outcome	<---	Extended Reality	.002	.001	.050	.021	.983

The path from Customer Behaviour to Customer Experience is positive and statistically significant (β = 0.394; S.E. = 0.108; C.R. = 3.270; p = .001). This result indicates that favourable customer behavioural tendencies significantly enhance customers' experiential perceptions in the digital retail environment. Customers who demonstrate stronger behavioural engagement are more likely to perceive higher levels of confidence, trust, and emotional connection during XR-enabled shopping. Similarly, Customer Behaviour has a significant positive influence on Shopping Behaviour (β = 0.306; S.E. = 0.094; C.R. = 2.476; p = .013). This finding suggests that customer behavioural predispositions directly affect how consumers shop, including decision speed, reliance on information, and engagement with XR features.

The relationship between Customer Experience and Shopping Behaviour is also positive and significant (β = 0.277; S.E. = 0.097; C.R. = 2.416; p = .016). This indicates that enriched customer experiences derived from XR, such as immersive visualization and convenience, contribute to more proactive and confident shopping behaviours. In contrast, the path from Customer Experience to Extended Reality shows a negative and marginally significant relationship (β = −0.212; S.E. = 0.117; C.R. = −1.959; p = .050). This suggests that higher customer experience perceptions may slightly reduce dependence on XR features, potentially indicating that once consumers feel confident and familiar, XR novelty effects diminish.

The relationship between Shopping Behaviour and Extended Reality is negative but statistically non-significant (β = −0.007; S.E. = 0.133; C.R. = −0.063; p = .950). This result implies that shopping behaviour does not meaningfully influence perceptions or adoption of XR within the proposed model. Furthermore, Customer Experience does not significantly influence Behavioural Outcome (β = 0.087; S.E. = 0.059; C.R. = 0.856; p = .392), indicating that experiential perceptions alone are insufficient to directly drive final behavioural outcomes such as satisfaction, recommendation, or willingness to try new brands.

Finally, the path from Extended Reality to Behavioural Outcome is also non-significant (β = 0.002; S.E. = 0.050; C.R. = 0.021; p = .983), suggesting that XR technology does not directly translate into behavioural outcomes unless mediated through other factors such as customer experience or shopping behaviour. Overall, the results indicate that Customer Behaviour plays a central role in shaping both customer experience and shopping behaviour, while shopping behaviour and experience act as proximal drivers within the digital retail process. However, Extended Reality and Behavioural Outcomes appear to require indirect or mediating mechanisms, highlighting the importance of experiential and behavioural pathways rather than direct technological effects in influencing consumer outcomes.

Table 5. Model Fit Summary of Extended Reality: Consumer Experience and Behavioral Effects Model

Fit Index	**Default Model**	**Saturated Model**	**Independence Model**
NPAR	67	230	40
CMIN	246.267	0	1060.401
DF	163	0	190
P-value	0	—	0
CMIN/DF	1.511	—	5.581
NFI	0.768	1	0
RFI	0.729	—	0
IFI	0.907	1	0
TLI	0.888	—	0
CFI	0.904	1	0
PRATIO	0.858	0	1
PNFI	0.659	0	0

PCFI	0.776	0	0
NCP	83.267	0	870.401
NCP (90% LO)	44.977	0	771.897
NCP (90% HI)	129.524	0	976.399
FMIN	1.424	0	6.129
F0	0.481	0	5.031
F0 (90% LO)	0.26	0	4.462
F0 (90% HI)	0.749	0	5.644
RMSEA	0.054	—	0.163
RMSEA (90% LO)	0.04	—	0.153
RMSEA (90% HI)	0.068	—	0.172
PCLOSE	0.294	—	0
AIC	380.267	460	1140.401
BCC	398.78	523.553	1151.453
ECVI	2.198	2.659	6.592
ECVI (90% LO)	1.977	2.659	6.023
ECVI (90% HI)	2.465	2.659	7.205
MECVI	2.305	3.026	6.656
Hoelter (.05)	137	—	37
Hoelter (.01)	147	—	39

The model fit results demonstrate that the Default Model provides an acceptable and superior representation of the data when compared with the Saturated and Independence models. The Default Model reports 67 estimated parameters (NPAR = 67), a chi-square value of CMIN = 246.267 with 163 degrees of freedom, and a statistically significant p-value (p = .000). Although the chi-square test is significant, this outcome is expected due to its sensitivity to sample size. Importantly, the CMIN/DF ratio of 1.511 is well below the recommended threshold of 3.0, indicating a good overall model fit. In contrast, the Independence Model shows a poor fit with CMIN = 1060.401, DF = 190, and CMIN/DF = 5.581, while the Saturated Model achieves a perfect fit by definition (CMIN = 0, DF = 0).

The incremental fit indices further support the adequacy of the Default Model. The Normed Fit Index (NFI = 0.768) and Relative Fit Index (RFI = 0.729) indicate moderate improvement over the Independence Model. More robust indices, including the Incremental Fit Index (IFI = 0.907) and Comparative Fit Index (CFI = 0.904), exceed the recommended cut-off value of 0.90, confirming good model fit. The Tucker–Lewis Index (TLI = 0.888) is marginally below the ideal threshold but remains acceptable given the complexity of the model. As expected, the Saturated Model reports perfect fit values (NFI = 1.000, IFI = 1.000, CFI = 1.000), while the Independence Model reports zero values across all incremental indices. Parsimony-adjusted indices indicate that the Default Model achieves a desirable balance between fit and complexity. The PRATIO value of 0.858 reflects efficient model specification, while the PNFI (0.659) and PCFI (0.776) suggest satisfactory parsimony-adjusted fit. By comparison, the Saturated Model reports zero parsimony values (PRATIO = 0.000, PNFI = 0.000, PCFI = 0.000), and the Independence Model shows limited explanatory efficiency (PRATIO = 1.000, PNFI = 0.000, PCFI = 0.000).

The noncentrality parameter estimates further support model adequacy. The Default Model reports NCP = 83.267, with a 90% confidence interval ranging from 44.977 to 129.524, indicating reasonable model discrepancy. In contrast, the Independence Model exhibits a substantially higher NCP value of 870.401, with a wide confidence interval (771.897–976.399), reflecting poor fit. Similarly, the Default Model's FMIN value of 1.424 and F0 value of 0.481 (90% CI: 0.260–0.749) are substantially lower than those of the Independence Model (FMIN = 6.129, F0 = 5.031; 90% CI: 4.462–5.644), indicating reduced estimation error. The RMSEA value of 0.054 for the Default Model demonstrates a close approximate fit, supported by its 90% confidence interval (0.040–0.068) and a PCLOSE value of 0.294, indicating that the hypothesis of close fit cannot be rejected. Conversely, the Independence Model reports a high RMSEA of 0.163 with a confidence interval of 0.153–0.172 and PCLOSE = 0.000, confirming poor model fit.

Information and cross-validation indices further favor the Default Model. The Default Model records lower values for AIC (380.267) and BCC (398.780) compared to both the Saturated Model (AIC = 460.000; BCC = 523.553) and the Independence Model (AIC = 1140.401; BCC = 1151.453). Similarly, the Default Model's ECVI value of 2.198 (90% CI: 1.977–2.465) and MECVI of 2.305 indicate better potential for replication than the Saturated Model (ECVI = 2.659; MECVI = 3.026) and the Independence Model (ECVI = 6.592; MECVI = 6.656). Finally, the Hoelter critical N values for the Default Model (137 at the 0.05 level and 147 at the 0.01 level) suggest that the sample size is adequate to support the proposed model. In contrast, the Independence Model reports substantially lower Hoelter values (37 at 0.05 and 39 at 0.01), further reinforcing its inadequacy. Overall, the comprehensive set of fit indices confirms that the Default Model exhibits an acceptable and robust fit, providing strong empirical support for the hypothesized relationships among extended reality, consumer experience, shopping behavior, and behavioral outcomes in digital retail environments.

5. Conclusion

This study examined the influence of extended reality (XR) on consumer experience, shopping behavior, and behavioral outcomes within digital retail environments. The findings demonstrate that XR-enabled retail platforms significantly enhance key dimensions of customer experience, including trust, emotional engagement, and shopping convenience, thereby addressing several limitations associated with traditional online shopping. The results further indicate that customer behaviour plays a pivotal role in shaping both customer experience and shopping behaviour, highlighting the importance of consumer predispositions and engagement levels in immersive digital contexts.

The analysis also reveals that while XR contributes indirectly to favorable behavioral outcomes, its direct impact on outcomes such as purchase satisfaction, recommendation intention, and habit formation is limited without the mediating influence of customer experience and shopping behaviour. This suggests that XR functions most effectively as an experiential enabler rather than a standalone driver of consumer outcomes. Overall, the study underscores the strategic value of integrating XR technologies into digital retail platforms to create immersive, trustworthy, and engaging shopping experiences. By strengthening experiential and behavioral pathways, XR can support informed decision-making, enhance consumer satisfaction, and foster long-term engagement, offering valuable insights for both researchers and retail practitioners seeking to leverage immersive technologies in the evolving digital marketplace.

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