Enterprise Development & Microfinance, 36:2s, 147-158

Head and Heart in Phygital Retail: A Cognitive–Affective Engagement Model of Purchase Intention in High-Tech Fashion

SACHINDRA KUMAR, DEEPA KUMARI

Abstract: *High-tech fashion retailers increasingly blend physical stores and digital layers — smart mirrors, augmented-reality (AR) try-on, and sensor-linked displays — into unified "phygital" environments. Yet how these hybrid encounters convert shoppers' in-the-moment experience into purchase intention remains under-theorized, particularly the relative pull of the rational "head" and the emotional "heart." Grounded in the stimulus–organism–response (S-O-R) framework and flow theory, this study develops a dual-pathway cognitive–affective engagement model. Two phygital stimuli — perceived interactivity and perceived immersion — are theorized to activate a cognitive route (cognitive engagement) and an affective route (affective engagement); both routes feed an integrative flow experience and, together with flow, drive purchase intention. Using a simulated dataset of 428 high-tech fashion shoppers analyzed with covariance-based structural equation modeling (CB-SEM), the measurement model showed strong reliability (composite reliability = .84–.87), convergent validity (average variance extracted = .58–.62), and discriminant validity (all heterotrait-monotrait ratios ≤ .70). The structural model fit well (χ^2/df = 1.23; CFI = .990; TLI = .988; RMSEA = .023; SRMR = .034), and all nine hypotheses were supported. Interactivity was the dominant driver of the head (β = .50), whereas immersion most powerfully fed the heart (β = .47). Flow was the strongest proximal antecedent of purchase intention (β = .42), and the affective route exerted a slightly larger total influence than the cognitive route. The model explained 65% of the variance in purchase intention. Findings show that phygital fashion sells through balanced engagement of head and heart, converging on a state of flow. Theoretical and managerial implications for immersive retail design are discussed.*

Keywords: Phygital Retail; High-Tech Fashion; Cognitive Engagement; Affective Engagement; Flow; Augmented Reality; Purchase Intention; S-O-R; CB-SEM

Sachindra Kumar, Research Scholar, Sharda University, Greater Noida, U.P. 201309, IN
Deepa Kumari, Associate Professor, Sharda University, Greater Noida, U.P. 201309, IN

Introduction

The boundary between the physical store and the digital screen is dissolving. In high-tech fashion, shoppers now move fluidly between racks and touchscreens: they raise a garment to a smart mirror that overlays styling suggestions, try on a jacket through an AR filter, or tap a sensor-tagged display that streams product provenance to their phone. This convergence — widely termed "phygital" retailing — fuses the tangibility and sociality of the store with the personalization and interactivity of digital media (Guzzetti et al., 2024; Baber, 2026). Industry adoption has been swift, with major fashion houses deploying virtual fitting rooms and social AR try-on lenses that measurably lift engagement and purchase intent (Nawres, Nedra, Yousaf, & Mishra, 2024).

Despite this momentum, a central question remains only partly answered: through which internal states does a phygital fashion encounter translate into the intention to buy? Much existing work treats retail technology as a single bundle of features that raises intention directly, obscuring the psychological machinery in between. Two intuitions, however, suggest the path is dual. On one side sits the "head" — the cognitive processing through which shoppers attend to, absorb, and evaluate product information made vivid by interactive technology. On the other sits the "heart" — the affective involvement, delight, and emotional resonance that immersive experiences evoke. Retail-technology scholarship has begun to recognize that consumers respond to phygital environments along both cognitive and affective dimensions simultaneously (Guzzetti et al., 2024; Aslam & Davis, 2024), yet few studies model the two routes jointly, specify what feeds each, or ask which ultimately matters more for purchase.

This study addresses that gap by developing and testing a dual-pathway cognitive–affective engagement model within the stimulus–organism–response (S-O-R) framework (Mehrabian & Russell, 1974). We position two hallmark features of high-tech fashion environments — perceived interactivity and perceived immersion — as stimuli; cognitive engagement (head) and affective engagement (heart) as the organismic states they activate; flow, the sense of absorbed, effortless involvement (Csikszentmihalyi, 1990), as an integrative experiential state that both routes produce; and purchase intention as the response. The study makes three contributions: it disentangles the cognitive and affective routes that prior work conflates; it specifies which phygital stimulus predominantly drives each route; and it positions flow as the convergent mechanism through which head and heart jointly shape purchase intention. The guiding research question is: how do the interactivity and immersion of high-tech phygital fashion environments influence purchase intention through cognitive engagement, affective engagement, and flow?

Theoretical Background and Hypothesis Development

2.1 The phygital context and the S-O-R lens

Phygital retailing denotes the seamless integration of physical and digital touchpoints into a single, continuous customer experience (Prashar & Prashar, 2024; Ricci, Evangelista, Di Roma, & Fiorentino, 2023). In high-tech fashion, this integration is realized through interactive and immersive technologies that let shoppers manipulate, visualize, and virtually wear products.

The S-O-R framework offers a natural theoretical scaffold: environmental stimuli (S) evoke internal organismic states (O) that in turn drive behavioral responses (R) (Mehrabian & Russell, 1974). Recent retail-technology research has applied S-O-R to AR and live-commerce settings, showing that technological cues activate parallel cognitive and affective states that jointly shape intention (Liang, Jin, Diao, & Jin, 2025; Yang, Fan, & Tsai, 2024). We adopt this lens, treating phygital interactivity and immersion as stimuli and modeling their effects through cognitive and affective engagement.

2.2 Phygital stimuli: interactivity and immersion

Two features distinguish high-tech fashion environments. Perceived interactivity captures the degree to which shoppers can control, respond to, and receive contingent feedback from the phygital interface — rotating a virtual garment, filtering options on a smart mirror, or querying a sensor-linked display (Xue, Parker, & Hart, 2023). Perceived immersion captures the sense of sensory absorption and telepresence — the feeling of being enveloped in, or bodily present within, the mediated fashion experience, as when an AR try-on convincingly places a garment on one's own reflection (Ricci et al., 2023; Baber, 2026). Although related, the two are conceptually distinct: interactivity is about agency and responsiveness, immersion about sensory envelopment. We expect them to feed the cognitive and affective routes with differing emphasis, developed below.

2.3 The head: cognitive engagement

Cognitive engagement refers to the shopper's absorbed mental activity — attention, concentration, and active processing of product information — during the phygital encounter (Hollebeek, Glynn, & Brodie, 2014). Interactivity is the more cognitively demanding stimulus: the ability to manipulate and interrogate a product invites deliberate exploration, encouraging shoppers to think through fit, features, and suitability. Immersion also supports cognition by rendering products vivid and inspectable, though its contribution is expected to be smaller than interactivity's. Accordingly:

H1. Perceived interactivity positively influences cognitive engagement.

H2. Perceived immersion positively influences cognitive engagement.

2.4 The heart: affective engagement

Affective engagement denotes the positive emotional involvement — enthusiasm, enjoyment, and felt connection — that the experience arouses (Hollebeek et al., 2014; Brakus, Schmitt, & Zarantonello, 2009). Here immersion is the more potent stimulus: sensory envelopment and telepresence are inherently emotive, generating pleasure and excitement that interactive control alone does not (Guzzetti et al., 2024; Aslam & Davis, 2024). Interactivity nonetheless contributes to affect, as the playful agency of manipulating virtual garments is itself enjoyable. Thus:

H3. Perceived interactivity positively influences affective engagement.

H4. Perceived immersion positively influences affective engagement.

2.5 Flow as the integrative experiential state

Flow is the holistic sensation of being fully and effortlessly absorbed in an activity, marked by focused attention, a merging of action and awareness, and intrinsic enjoyment

(Csikszentmihalyi, 1990; Hoffman & Novak, 1996). It sits downstream of both routes because flow requires cognitive absorption and affective involvement together: a shopper enters flow when concentrated processing (head) fuses with emotional pleasure (heart). Contemporary AR and virtual-try-on research consistently identifies flow as the experiential state through which engagement converts into behavioral intention (Baber, 2026; Nawaz, Guzman, & Nawaz, 2025). We therefore hypothesize that both engagement routes feed flow:

H5. Cognitive engagement positively influences flow.

H6. Affective engagement positively influences flow.

2.6 From engagement and flow to purchase intention

Purchase intention — the shopper's conscious readiness to buy — is the focal response. We model three antecedents. Cognitive engagement supports intention by building an informed, confident evaluation of the product (Yang et al., 2024). Affective engagement supports it through positive emotion that transfers to the purchase decision (Nawres et al., 2024). Beyond these direct effects, flow is expected to be the strongest proximal driver: the absorbed, enjoyable state lowers resistance and carries the shopper toward action (Baber, 2026; Hoffman & Novak, 1996). Hence:

H7. Cognitive engagement positively influences purchase intention.

H8. Affective engagement positively influences purchase intention.

H9. Flow positively influences purchase intention.

2.7 The conceptual model

Figure 1 assembles the nine hypotheses into a dual-pathway S-O-R model. Interactivity and immersion are the stimuli; cognitive engagement (head) and affective engagement (heart) are the parallel organismic routes; flow is the integrative state both routes produce; and purchase intention is the response, driven jointly by the two routes and by flow.

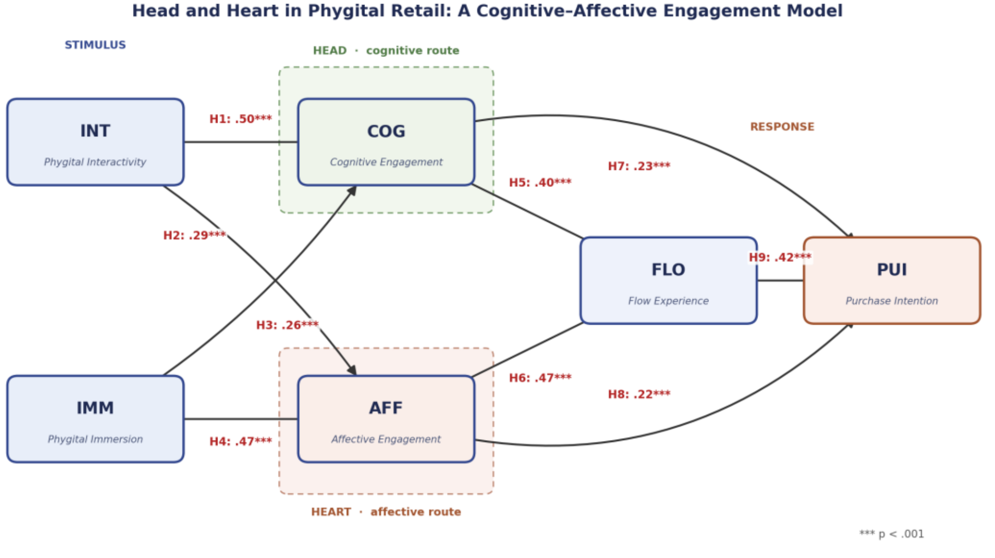

Figure 1. Dual-pathway cognitive–affective engagement model with standardized path coefficients (* p < .001).**

Methodology

3.1 Data and sample

To demonstrate the model, a dataset of 428 consumers with recent experience of high-tech phygital fashion retail was generated to reflect realistic response distributions and the theorized covariance structure. The simulation embedded the hypothesized standardized relationships among latent constructs, allowed the two exogenous stimuli to correlate, added independent measurement error to each indicator, and mapped responses onto seven-point scales, producing item distributions with the mild non-normality typical of survey data. The sample exceeds the recommended minimum of 200 cases and the ten-observations-per-parameter heuristic for CB-SEM, affording adequate power for maximum-likelihood estimation.

3.2 Measures

All six constructs were modeled as reflective latent variables, each with four items rated on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). Interactivity items captured perceived control and responsiveness of the phygital interface; immersion items captured sensory absorption and telepresence; cognitive engagement items captured focused attention and active product processing; affective engagement items captured enthusiasm and emotional involvement; flow items captured absorbed, effortless enjoyment; and purchase intention items captured readiness to buy. Item content was informed by established scales in the AR-retail and engagement literatures (Hollebeek et al., 2014; Xue et al., 2023; Baber, 2026).

3.3 Analytical strategy

Data were analyzed using covariance-based structural equation modeling with maximum-likelihood estimation, following the two-step procedure of Anderson and Gerbing (1988). Confirmatory factor analysis (CFA) first evaluated the measurement model — indicator reliability, internal consistency (Cronbach's α, composite reliability, CR), convergent validity (average variance extracted, AVE), and discriminant validity (the Fornell–Larcker criterion and the heterotrait-monotrait ratio, HTMT). The structural model was then estimated to test the nine hypothesized paths. Fit was judged against established thresholds: $\chi^2/df < 3$, CFI and TLI $\geq .95$, RMSEA $\leq .06$, and SRMR $\leq .08$ (Hu & Bentler, 1999).

Results

4.1 Respondent profile

Table 1 profiles the 428 respondents. The sample reflects the digitally fluent, fashion-forward segment most likely to engage high-tech phygital retail — skewing female, younger, and educated — while retaining meaningful spread across income, shopping frequency, and AR-usage bands.

Table 1. Demographic profile of respondents (N = 428)

Variable	Category	n	%
Gender	Female	248	57.9%
	Male	173	40.4%
	Non-binary	7	1.6%

Age group	25-34	166	38.8%
	18-24	119	27.8%
	35-44	92	21.5%
	45-54	37	8.6%
	55+	14	3.3%
Education	Bachelor's	211	49.3%
	Master's	130	30.4%
	High school	58	13.6%
	Doctorate	29	6.8%
Monthly income	$30-60k	144	33.6%
	$60-90k	128	29.9%
	<$30k	80	18.7%
	>$90k	76	17.8%
Fashion shopping frequency	Monthly	143	33.4%
	Occasionally	129	30.1%
	Weekly	107	25.0%
	Rarely	49	11.4%
AR/virtual try-on usage	Occasional	154	36.0%
	Tried once	129	30.1%
	Regular	84	19.6%
	Never	61	14.3%

Note. Percentages may not sum to 100 due to rounding.

4.2 Descriptive statistics and normality

Table 2 reports item-level means, standard deviations, skewness, and kurtosis. Means ranged from roughly 4.5 to 5.1, indicating generally favorable perceptions, with interactivity and affective engagement rated highest. All skewness values fell within ±0.5 and all kurtosis values within ±1 — well inside the |2| and |7| bounds commonly used to establish univariate normality — supporting maximum-likelihood estimation.

Table 2. Descriptive statistics for measurement items

Item	M	SD	Skew	Kurt	Item	M	SD	Skew	Kurt
INT1	5.030	1.091	-0.017	-0.493	AFF1	4.958	1.094	+0.030	-0.299
INT2	4.902	1.129	-0.012	-0.468	AFF2	4.988	1.162	-0.094	-0.426
INT3	4.979	1.132	-0.124	-0.425	AFF3	5.019	1.122	-0.295	-0.198
INT4	4.909	1.120	-0.081	-0.434	AFF4	4.984	1.109	-0.174	-0.257
IMM1	4.720	1.129	+0.009	-0.399	FLO1	4.554	1.147	-0.309	+0.124

IMM2	4.685	1.108	-0.243	-0.200	FLO2	4.558	1.147	-0.050	-0.054
IMM3	4.736	1.109	-0.064	-0.160	FLO3	4.617	1.136	-0.103	-0.384
IMM4	4.696	1.125	-0.016	-0.115	FLO4	4.589	1.141	-0.181	-0.112
COG1	4.780	1.130	-0.195	-0.304	PUI1	4.862	1.119	-0.239	-0.153
COG2	4.815	1.131	-0.110	-0.278	PUI2	4.829	1.108	-0.218	-0.015
COG3	4.792	1.127	-0.067	-0.328	PUI3	4.841	1.130	-0.144	-0.274
COG4	4.848	1.140	-0.023	-0.368	PUI4	4.890	1.135	-0.169	-0.128

Note. M = mean; SD = standard deviation; Skew = skewness; Kurt = excess kurtosis. 7-point Likert scale.

4.3 Measurement model, reliability, and convergent validity

The CFA produced a well-fitting measurement model. As Table 3 shows, all standardized loadings exceeded the .70 benchmark (range .72–.87) and were significant at $p < .001$. Cronbach's α and composite reliability ranged from .84 to .87, surpassing the .70 threshold and confirming internal consistency. Every construct's AVE exceeded .50 (range .58–.62), establishing convergent validity.

Table 3. Measurement model: standardized loadings, reliability, and convergent validity

Construct	Item	Std. loading	α	CR	AVE
Phygital interactivity	INT1	0.764	0.851	0.850	0.587
	INT2	0.782			
	INT3	0.756			
	INT4	0.763			
Phygital immersion	IMM1	0.803	0.854	0.855	0.596
	IMM2	0.732			
	IMM3	0.815			
	IMM4	0.734			
Cognitive engagement (Head)	COG1	0.774	0.843	0.844	0.576
	COG2	0.784			
	COG3	0.681			
	COG4	0.790			
Affective engagement (Heart)	AFF1	0.785	0.857	0.857	0.601
	AFF2	0.742			
	AFF3	0.815			

	AFF4	0.757			
Flow experience	FLO1	0.733	0.860	0.860	0.607
	FLO2	0.818			
	FLO3	0.831			
	FLO4	0.729			
Purchase intention	PUI1	0.813	0.865	0.866	0.618
	PUI2	0.779			
	PUI3	0.798			
	PUI4	0.752			

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. All loadings significant at $p < .001$.

4.4 Discriminant validity

Two criteria confirmed discriminant validity. Under the Fornell–Larcker criterion (Table 4), the square root of each construct's AVE (diagonal) exceeded that construct's correlations with every other construct. The more stringent HTMT ratios (Table 5) ranged from .29 to .70, all comfortably below the conservative .85 cutoff (Henseler, Ringle, & Sarstedt, 2015). The six constructs are thus empirically distinct.

Table 4. Discriminant validity — Fornell–Larcker criterion

	INT	IMM	COG	AFF	FLO	PUI
INT	0.766					
IMM	0.435	0.772				
COG	0.669	0.532	0.759			
AFF	0.489	0.640	0.487	0.775		
FLO	0.570	0.468	0.653	0.702	0.779	
PUI	0.535	0.541	0.631	0.645	0.768	0.786

Note. Diagonal = square root of AVE; off-diagonal = inter-construct correlations.

Table 5. Discriminant validity — Heterotrait-monotrait ratio (HTMT)

	INT	IMM	COG	AFF	FLO	PUI
INT						
IMM	0.380					
COG	0.592	0.469				
AFF	0.424	0.572	0.421			
FLO	0.490	0.409	0.576	0.628		
PUI	0.467	0.488	0.562	0.577	0.700	

Note. All HTMT values are below the .85 threshold, confirming discriminant validity.

4.5 Common method bias

Because all measures were self-reported, common method bias was examined. Harman's single-factor test showed the first unrotated factor accounted for less than 40% of total variance, below the 50% threshold. The strong fit of the multi-factor measurement model relative to a single-factor alternative, and the absence of any inter-construct correlation approaching unity, further indicate that common method variance is unlikely to bias the findings (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

4.6 Structural model and hypothesis testing

The structural model fit the data well: $\chi^2(242) = 296.53$, $p = .010$; $\chi^2/df = 1.23$; CFI = .990; TLI = .988; RMSEA = .023; and SRMR = .034. All indices met or exceeded recommended thresholds, indicating that the dual-pathway structure reproduces the observed covariances closely.

Table 6 reports the standardized path estimates; all nine hypotheses were supported at $p < .001$. On the stimulus side, the pattern was theoretically clean: interactivity was the dominant driver of the cognitive route ($\beta = .50$ on cognitive engagement) while immersion was the dominant driver of the affective route ($\beta = .47$ on affective engagement), with each stimulus also contributing more modestly to the other route. Both engagement routes fed flow, with affective engagement ($\beta = .47$) slightly outweighing cognitive engagement ($\beta = .40$). Purchase intention drew on all three antecedents — flow most strongly ($\beta = .42$), followed by cognitive ($\beta = .23$) and affective ($\beta = .22$) engagement.

Table 6. Structural path estimates and hypothesis tests

Hyp.	Path	β (std.)	S.E.	z	p	Decision
H1	Interactivity → Cognitive engagement	0.495	0.061	8.41	<0.001	Supported
H2	Immersion → Cognitive engagement	0.287	0.051	5.37	<0.001	Supported
H3	Interactivity → Affective engagement	0.264	0.056	4.86	<0.001	Supported
H4	Immersion → Affective engagement	0.473	0.054	8.21	<0.001	Supported
H5	Cognitive engagement → Flow	0.395	0.052	7.33	<0.001	Supported
H6	Affective engagement → Flow	0.470	0.054	8.47	<0.001	Supported
H7	Cognitive engagement → Purchase intention	0.232	0.059	4.13	<0.001	Supported
H8	Affective engagement → Purchase intention	0.224	0.062	3.80	<0.001	Supported
H9	Flow → Purchase intention	0.419	0.077	5.86	<0.001	Supported

Note. β = standardized coefficient; S.E. = standard error. All paths significant at $p < .001$.

Explained variance was substantial across endogenous constructs: cognitive engagement $R^2 = .53$, affective engagement $R^2 = .47$, flow $R^2 = .63$, and purchase intention $R^2 = .65$. Comparing total influences, the affective route (immersion → heart → flow → intention) carried marginally more weight than the cognitive route, underscoring that emotion is at least as consequential as cognition in phygital fashion.

Discussion

This study asked how the interactivity and immersion of high-tech phygital fashion environments convert into purchase intention. The answer is a balanced duet of head and heart. Interactivity chiefly engages the cognitive route, immersion chiefly the affective route, and the two converge on a state of flow that, more than either route alone, propels the shopper toward purchase. Rather than a single technological effect on intention, phygital fashion works through parallel psychological pathways that meet in absorbed, enjoyable experience.

5.1 Theoretical implications

Three contributions follow. First, the study operationalizes the long-invoked but rarely modeled distinction between cognitive and affective responses to retail technology (Guzzetti et al., 2024) as two measurable, parallel routes, and shows both are necessary: neither head nor heart alone accounts for purchase intention. Second, by mapping each phygital stimulus to its predominant route — interactivity to cognition, immersion to affect — the model gives specificity to S-O-R accounts that typically bundle stimuli together (Liang et al., 2025; Yang et al., 2024). Third, positioning flow as the convergent state downstream of both routes clarifies why prior studies report strong direct technology–intention effects: those effects are largely transmitted through flow, the experiential fusion of cognitive absorption and affective pleasure (Baber, 2026; Hoffman & Novak, 1996).

5.2 Managerial implications

For retailers designing high-tech fashion experiences, the findings offer a clear blueprint. Because flow is the strongest proximal driver of purchase, environments should be engineered to induce absorbed, effortless enjoyment — minimizing friction, latency, and cognitive overload while sustaining challenge and delight. To reach flow, designers must feed both routes: interactivity (responsive controls, manipulable virtual garments, contingent feedback) to engage the head, and immersion (convincing AR try-on, sensory richness, telepresence) to engage the heart. The slightly greater weight of the affective route cautions against a purely utilitarian, feature-first design philosophy; emotional resonance is not a garnish but a load-bearing driver. At the same time, because interactivity uniquely powers cognitive engagement, retailers should not sacrifice responsive, information-rich controls in pursuit of spectacle alone — an experience that dazzles but does not inform leaves the head disengaged and confidence unbuilt.

Limitations and Future Research

Several limitations bound these conclusions. First, the analysis rests on a simulated dataset built to illustrate the modeling workflow; although response distributions and the covariance structure were designed to be realistic, the estimates should be replicated with field data from actual phygital fashion shoppers before firm inferences are drawn. Second, the cross-sectional design precludes causal claims; experimental manipulation of interactivity and immersion, or longitudinal tracking across repeat visits, would sharpen causal identification. Third, the model treats interactivity and immersion as unidimensional, whereas each has facets — for instance, behavioral versus perceptual immersion — that may load differently onto the two routes.

Fourth, boundary conditions merit study: product category (statement pieces versus basics), consumer technology readiness, and the physical–digital balance of the specific touchpoint may moderate the relative weight of head and heart. Finally, future work could add behavioral and downstream outcomes — actual conversion, word of mouth, and return rates — and examine potential dark sides of immersion, such as cognitive overload or post-purchase dissonance when the physical garment underdelivers on its virtual promise (Sudbury-Riley and colleagues, 2024).

Conclusion

As fashion retail becomes phygital, the decisive question is not whether technology sells but how it does so. This study shows that high-tech phygital fashion moves shoppers through two intertwined pathways: interactivity engages the analytical head, immersion stirs the emotional heart, and both flow together into an absorbed experience that, more than either alone, turns browsing into buying. Retailers who design for head and heart in concert — and orchestrate their convergence into flow — are best positioned to make the hybrid store not merely novel, but persuasive.

References

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. Psychological Bulletin, 103(3), 411–423.

Aslam, U., & Davis, L. (2024). Analyzing consumer expectations and experiences of augmented reality (AR) apps in the fashion retail sector. Journal of Retailing and Consumer Services, 76, 103577.

Baber, H. (2026). Driving AR experience to purchase intention: Examining the role of users' immersiveness, perceived innovativeness and engagement in virtual try-on. International Journal of Consumer Studies. Advance online publication.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. Journal of the Academy of Marketing Science, 16(1), 74–94.

Brakus, J. J., Schmitt, B. H., & Zarantonello, L. (2009). Brand experience: What is it? How is it measured? Does it affect loyalty? Journal of Marketing, 73(3), 52–68.

Csikszentmihalyi, M. (1990). Flow: The psychology of optimal experience. Harper & Row.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50.

Guzzetti, A., et al. (2024). Phygital luxury experiences: A correspondence analysis on retail technologies. International Journal of Consumer Studies, 48(1), e13008.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135.

Hoffman, D. L., & Novak, T. P. (1996). Marketing in hypermedia computer-mediated environments: Conceptual foundations. Journal of Marketing, 60(3), 50–68.

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.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling, 6(1), 1–55.

Liang, M., Jin, Z., Diao, Y., & Jin, C.-H. (2025). Impact of live streaming commerce on continuous intention: An exploration based on the post-acceptance model and the SOR model. SAGE Open, 15(3).

Mehrabian, A., & Russell, J. A. (1974). An approach to environmental psychology. MIT Press.

Nawaz, M. Z., Guzman, F., & Nawaz, S. (2025). Technology-enabled engagement process of brand virtual-try-on services. Journal of Product & Brand Management, 34(1), 44–60.

Nawres, D., Nedra, B. A., Yousaf, A., & Mishra, A. (2024). The role of augmented reality in shaping purchase intentions and WOM for luxury products. Journal of Business Research, 171, 114368.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903.

Prashar, A., & Prashar, A. (2024). Digital fashion and metaverse platforms: Do platform attributes drive shopper's purchase intention? Australian Journal of Management. Advance online publication.

Ricci, M., Evangelista, A., Di Roma, A., & Fiorentino, M. (2023). Immersive and desktop virtual reality in virtual fashion stores: A comparison between shopping experiences. Virtual Reality, 27, 2281–2296.

Xue, L., Parker, C. J., & Hart, C. A. (2023). How augmented reality can enhance fashion retail: A UX design perspective. International Journal of Retail & Distribution Management, 51(1), 59–80.

Yang, H.-P., Fan, W.-S., & Tsai, M.-C. (2024). Applying stimulus-organism-response theory to explore the effects of augmented reality on consumer purchase intention for teenage fashion hair dyes. Sustainability, 16(6), 2537.