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Determinants of Learning Persistence in Open Universities: An Extended S-O-R Perspective

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Abstract

Purpose: Grounded in the Extended Stimulus-Organism-Response (S-O-R) framework, this study investigates the mechanistic pathways driving learning persistence in the Open University context to address chronic attrition. It integrates the IS Success Model to examine how external system characteristics and internal psychological schemas jointly influence student commitment in distance education. **Research design, data and methodology:** Data were collected from 502 first-semester undergraduates at Yunnan Open University through quota and purposive sampling, utilizing an 80-point screening criterion. Methodological rigor was ensured using HTMT ratios for discriminant validity and 5,000-resample bootstrapping for mediation analysis within a structural equation model (SEM). **Results:** The model explains 35.7% of the variance in persistence. Internal (Sense of Belonging and Academic Self-Efficacy) and external (Information Quality and Service Quality) stimuli significantly initiate multidimensional engagement, acting as a dual-path mediation mechanism toward persistence. Notably, emotional engagement (β=0.383) emerged as a more potent predictor than cognitive engagement (β=0.370) **Conclusions:** Learning persistence is governed by a dual-track mechanism of "technical enablement" and "psychological triggering," theoretically advancing the S-O-R paradigm. While acknowledging potential selection bias from the purposive sampling of high-performing students, the study suggests institutional support should prioritize community-building to stimulate emotional investment, mitigating initial transition shock for adult learners.

Keywords: Learning Persistence; SOR; OULP, Open Education; Sense of Belonging

JEL Classification Code: I21, I23, O33

1. Introduction

The global expansion of higher education is increasingly defined by its digital transformation, a trend accelerated by the post-pandemic proliferation of Massive Open Online Courses (MOOCs) and digital platforms (Cheng, 2025b; Jung & Lee, 2018; Kuo et al., 2021). Within the lifelong learning ecosystem, Open Universities (OUs) serve as the backbone of degree-oriented continuing education. By offering open admission and flexible credit systems, OUs cater primarily to adult learners facing temporal-spatial separation from traditional campuses. However, this expansion is shadowed by a persistent completion crisis. The UNESCO 2026 Global Education Monitoring Report indicates that while tertiary enrollment ratios doubled from 2000 to 2024, first-degree completion rates lagged significantly, rising from only 17% to 27% (Businessday, 2026).

The phenomenon of attrition is particularly acute in Open and Distance Learning (ODL) environments, where total course dropout rates historically range between 40% and 80%, substantially higher than traditional face-to-face settings (Fu, 2022). Although the National Open University of China (OUC) reports a relatively stable cumulative completion rate of 76% at the macro level (Xiao et al., 2025), rigorous longitudinal analyses reveal dropout rates reaching up to 30% (Xiao et al., 2025). Furthermore, pronounced regional disparities exist within provincial branches (Tang et al., 2022). Institutions such as Yunnan Open University face

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critical challenges in maintaining stable learning ecosystems, highlighting an urgent need to optimize retention strategies tailored to localized ODL contexts.

Despite extensive literature addressing online learning dropout, a critical gap persists in the theoretical explanation of departure mechanisms. Recent scholarship criticizes the over-reliance on "dead-end" demographic variables (e.g., age, gender) and broad structural drivers (e.g., time poverty) to explain attrition (Lal et al., 2025; Xavier, n.d.). While demographic factors proxy structural inequality, they fail to elucidate the underlying psychological processes of how adult learners interact with institutional support (Lal et al., 2025). Consequently, there is a distinct lack of mechanistic explanations detailing how external technological environments interact with a learner's internal psychological baselines to facilitate multidimensional engagement and, ultimately, long-term persistence (Amir et al., 2021; Susoy, 2026).

To bridge this mechanistic gap, this study adopts the Extended Stimulus-Organism-Response (S-O-R) framework. Diverging from classical models, the extended framework classifies stimuli into a dual-track system (PhD Assistance, 2026). Drawing on the Information Systems (IS) Success Model (DeLone & McLean, 2003), Information Quality (IQ) and Service Quality (SQ) are conceptualized as External Stimuli—the exteroceptive technological cues provided by the platform (Sann et al., 2024). Conversely, Academic Self-Efficacy (ASE) and Sense of Belonging (SOB) are reconceptualized as Internal Stimuli. Recent social cognition research validates that these pre-existing psychological schemas function as "mental codes" and internal baselines that activate prior to, and independent of, the immediate technological interaction (Janczyk et al., 2020; Kentucky Department of Education, 2023). This dual-track system provides a robust lens to observe how external and internal stimuli jointly initiate the “Organism”—a processing phase characterized by cognitive and emotional engagement (Li & Zin, 2026; Tshibwabwa & Madal, 2025)—which subsequently predicts the behavioral response of Learning Persistence.

Empirically, this study isolates its sample to first-semester undergraduates utilizing Yunnan Open University's learning platform. The rationale for this specific cohort is grounded in "Transition Shock" theory (Bayaga et al., 2022). Adult learners face the highest risk of departure during their initial transition due to technical cognitive overload and epistemic misalignment (Brown et al., 2015; Mthombeni, 2026). Empirical evidence demonstrates that over 50% of total higher education attrition occurs during the first year (Kahn, 2016). By targeting this critical transition window, the study mitigates confounding variables associated with late-stage dropout and captures the foundational interaction patterns that establish long-term persistence.

The marginal contributions of this study are three-fold.

First, regarding the theoretical contribution, by applying the Extended S-O-R paradigm, this study conceptually differentiates pre-existing individual traits as Internal Stimuli from system characteristics (External Stimuli). This resolves the classification ambiguities in prior ODL research and provides a robust architecture for understanding the dual drivers of learner behavior.

Second, with respect to the contextual contribution, by utilizing empirical data from Yunnan Open University, this research moves beyond macro-level demographic descriptions to identify the precise system-level mechanisms (IQ, SQ) necessary to support adult learners navigating regional disparities and physical isolation.

Third, in terms of the methodological contribution, employing Structural Equation Modeling (SEM) with bootstrapping techniques, this study precisely decomposes the specific indirect effects of cognitive and emotional engagement. This approach rigorously quantifies the predictive pathways of persistence, respecting the inferential boundaries of cross-sectional data without overstating causal determinism.

2. Literature Review

2.1 Theoretical Foundation: The Extended S-O-R Framework

This study adopts the Stimulus-Organism-Response (S-O-R) paradigm as its theoretical foundation. Originally proposed by Russell and Mehrabian (1974), the classic model posited that external environmental cues (Stimulus) alter an individual's internal psychological state (Organism), which in turn induces behavioral responses (Response) characterized by approach or avoidance (Liu & Zheng, 2019; Souki et al., 2026). However, as research in Information Systems (IS) and online learning has matured, scholars emphasize that human behavior is simultaneously influenced by internal psychological configurations that exist prior to the stimulus-event (Kim & Lennon, 2013; Liu & Zheng, 2019). Consequently, this study employs the "Extended S-O-R Framework," which categorizes stimuli into a dual-track system: internal trait-based stimuli (pre-existing schemas) and external environmental stimuli (system characteristics) (Piligrimienė et al., 2020; Shang & Lyv, 2024). This extended framework has been widely applied to explore how digital instructional environments and learners' psychological baselines jointly shape learning behaviors (Cheng, 2024, 2025b; Khan et al., 2024).

2.2 Internal Stimuli: Academic Self-Efficacy and Sense of Belonging

In technology-mediated learning, internal stimuli are factors originating from learners' inner selves, functioning as baseline inputs that precede and filter subsequent cognitive and emotional processing (Shang & Lyv, 2024).

Academic Self-efficacy (ASE) refers to an individual's confidence in their ability to organize and execute actions required to achieve specific goals (Bandura, 1977). As a core component of Social Cognitive Theory, it serves as a vital mediator linking motivation to behavior (Cho & Shen, 2013). While traditionally viewed as an outcome, within the extended S-O-R paradigm, ASE is formally modeled as a person-related internal stimulus (Huang, 2023). It represents a pre-existing psychological schema that dictates the subjective appraisal of external tasks. According to social influence research, self-efficacy intuitively predicts a main effect on perceived personal competency before actual task engagement (Lucas et al., 2006). Thus, ASE functions not as a reaction to the platform, but as a baseline internal force that stimulates the inner perceptual state of the user (Huang, 2023; Yang et al., 2022).

Sense of Belonging (SOB) is defined as the experience of personal involvement in an environment that makes individuals feel like an indispensable part of it (Cheung & Lee, 2012; Goodenow, 1993). As Maslow (1962) proposed, the need for belonging often surpasses the desire for knowledge. In digital learning environments, SOB is re-conceptualized as a "social interaction stimulus" (Hongsuchon et al., 2025). It represents a prior climate perception or an internalized fraction of the social environment (Longstaff, 1996). Pre-existing social perceptions function as initial stimuli to circumvent purely rational decision-making, directly initiating organismic states such as flow and emotional attachment (Chang, 2022; Hongsuchon et al., 2025).

2.3 External Stimuli: Information Quality and Service Quality

External stimuli in this study represent the exteroceptive cues provided by the digital platform's infrastructure (Longstaff, 1996). The Information System Success Model (DeLone & McLean, 2003) identifies the significant role of Information Quality (IQ) and Service Quality (SQ) in user evaluations. With the rapid advancement of information technology, these system characteristics have become integral stimuli in e-learning environments. Cheng (2014) and Panigrahi et al. (2021) point out that these external system stimuli significantly impact learners' multi-dimensional engagement, though the specific mechanisms differentiating their effects on affective versus cognitive engagement require deeper exploration.

2.4 Organism: Cognitive and Emotional Engagement

The "Organism" phase captures the proximal, transient psychological processing states induced by the dual-track stimuli (Souki et al., 2026).

Cognitive Engagement (CE) reflects the extent to which learners strategically deploy cognitive resources, involving deep content processing and active thinking (Greene & Azevedo, 2007; Henrie et al., 2015). In digital settings, this engagement is driven by high motivation levels and effective self-regulation strategies (Zimmerman, 2000).

Emotional Engagement (EE) involves learners' affective reactions, spanning positive and negative responses such as interest and belonging toward instructors and peers (Fredricks et al., 2004; Furlong et al., 2003; Reschly & Christenson, 2022). Although interactive designs can elevate engagement (Sun & Rueda, 2012), challenges like isolation persist (Artino Jr., 2012). Both forms of engagement serve as critical organismic mediators linking internal and external stimuli to long-term outcomes.

2.5 Response: Learning Persistence

The final "Response" is characterized by approach behaviors signifying positive engagement with the stimulus (Souki et al., 2026). In this study, Learning Persistence (LP) is the behavioral manifestation of this approach mechanism. While some scholars define it as the willingness to complete a current course (Schmitz et al., 2011; You, 2018) or the intention for future studies (Mitchell, 2015), this study defines LP as students' continual enrollment in successive semesters (Nam & Song, 2024), representing the ultimate behavioral outcome of the S-O-R chain.

3. Research Methods and Materials

3.1 Research Framework

Based on the Extended S-O-R paradigm, this study constructs a conceptual framework (Figure 1) comprising seven latent variables. To address the complex interplay between learner psychology and system architecture, the initial "Stimulus" phase is explicitly operationalized as a dual-track system.

Specifically, regarding the trait track, Internal Stimuli comprising Academic Self-Efficacy (ASE) and Sense of Belonging (SOB) serve as pre-existing internal psychological schemas and prior climate perceptions (Piligrimienė et al., 2020; Shang & Lyv, 2024). They function as interoceptive stimuli (Longstaff, 1996) that determine the individual's subjective baseline prior to task engagement. Simultaneously, within the system track, External Stimuli including Information Quality (IQ) and Service Quality (SQ), derived from the IS Success Model, serve as external environmental cues or exteroceptive stimuli representing the digital platform's physical and service infrastructure (Longstaff, 1996).

These dual-track stimuli simultaneously elicit proximal, transient internal reactions within the "Organism", specifically Cognitive Engagement (CE) and Emotional Engagement (EE) (Chang, 2022; Souki et al., 2026). Ultimately, these concurrent processing states drive the "Response", defined here as Learning Persistence (LP), an approach behavior manifesting the student's ongoing commitment to the learning process (Souki et al., 2026).

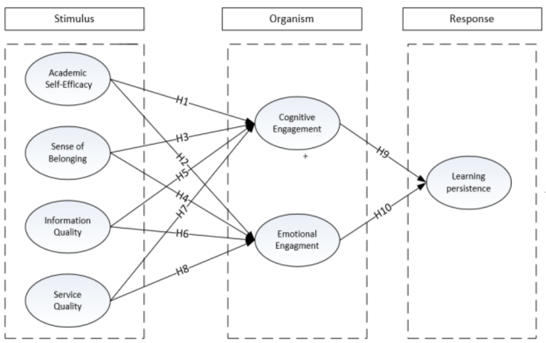

Figure 1: Conceptual Framework

Integrating seven latent variables within the SOR framework, this study examines four stimuli (ASE, SOB, IQ, and SQ), two organism mediators (cognitive and emotional engagement), and learning persistence as the behavioral response. Focusing on undergraduates at Yunnan Open University, the research investigates the causal interactions and synergistic effects among these constructs. Based on this conceptual framework, the following hypotheses are proposed:

H_a1 Academic Self-efficacy has an influence on Cognitive Engagement.

H_a2 Academic Self-efficacy has an influence on Emotional Engagement.

H_a3 Sense of Belonging has an influence on Cognitive Engagement.

H_a4 Sense of Belonging has an influence on Emotional Engagement.

H_a5 Information Quality has an influence on Cognitive Engagement.

H_a6 Information Quality has an influence on Emotional Engagement.

H_a7 Service Quality has an influence on Cognitive Engagement.

H_a8 Service Quality has an influence on Emotional Engagement.

H_a9 Cognitive Engagement has an influence on Learning Persistence.

H_a10 Emotional Engagement has an influence on Learning Persistence.

3.2 Research Methodology

This study employed a quota sampling method integrated with purposive sampling to select respondents. Initially, quota sampling was implemented across three specific majors with a 40% sampling fraction to ensure structural representativeness. To ensure that participants possessed sufficient experience with the OULP platform, a purposive screening criterion was applied: students were required to have obtained a score of 80 or above in the course Fundamentals of Open Education Learning. This 80-point threshold, automatically generated from five engagement dimensions (videos, assignments, forums, reports, and live sessions), ensured that respondents were comprehensively experienced users. While this criterion minimizes random response bias, its potential selection bias toward highly engaged learners is acknowledged as a study limitation.

The measurement instrument was adapted from established scales and underwent a rigorous back-translation process to ensure linguistic and contextual equivalence within the Open University setting. All latent constructs were measured using a five-point Likert scale. Content validity was verified by four experts with over 10 years of educational research experience, yielding an Item-Objective Congruence (IOC) index above the recommended thresholds. A subsequent pilot test with 50 students demonstrated excellent internal consistency, with all Cronbach's Alpha coefficients exceeding 0.80 (DeVellis & Thorpe, 2021).

Regarding data collection and ethics, the study received formal approval from the Institutional Review Board (IRB). Written informed consent was obtained electronically, and participants were informed of their right to withdraw at any time without penalty. For statistical analysis, data were first screened for multivariate normality, multicollinearity (VIF), and common method bias (CMB). Confirmatory Factor Analysis (CFA) and the Heterotrait-Monotrait (HTMT) ratio were utilized to establish measurement model integrity. Finally, Structural Equation Modeling (SEM) with a 5,000-resample bootstrapping procedure was employed to test the hypothesized paths and quantify mediation effects.

3.3 Population and Sample Size

The target population for this survey consisted of undergraduate students enrolled in three specific majors at Yunnan Open University: Law, Computer Science, and Administrative Management. Based on the Structural Equation Modeling (SEM) framework and the scale of latent variables In this study, a minimum sample size of 425 was recommended, following the recommendation of Soper's (2026) SEM sample size calculator.

Considering the common response rate issues associated with adult online learners, and to ensure that the final analytical sample possessed sufficient validity and representativeness, a rigorous process of screening, filtering, and non-probability sampling was implemented. To maintain the structural integrity of the target population, this study employed a quota sampling technique with a fixed sampling fraction of 40% across all three majors (Creswell & Creswell, 2017). A total of 700 questionnaires were distributed to the target pool. From these, 675 responses were returned, and 502 valid cases were retained after screening (Section 4.1). Table 1 (Panel A) provides detailed information on the sampling distribution across the specific majors.

Table 1 Sampling Distribution and Demographic Profile

Panel A: Sampling by Major	Population (N)	Distributed Sample	Valid Sample (N=502)	Percentage (%)
Law	587	235	177	35.3
Computer Sci. & Tech	657	263	219	43.6
Administrative Management	505	202	106	21.1
Total	1749	700	502	100.0
Panel B: Demographic Profile	**Category**		**Frequency**	**Percentage (%)**
Gender	Male		227	45.2
	Female		275	54.8
Age	18-25		98	19.5
	26-30		186	37.1
	31-40		128	25.5
	41-50		63	12.5
	Above 50		27	5.4
Frequency of Use	Once a week		32	6.4
	Several times a week		141	28.1
	Once a day		229	45.6
	Several times a day		100	19.9

4. Results

4.1 Demographic Information

A total of 675 questionnaires were collected. To ensure data quality and mitigate response bias, a rigorous data screening process was conducted. Specifically, 173 responses were excluded based on three predefined criteria: (1) failed attention checks embedded in the survey; (2) straight-lining or patterned responses indicating a lack of cognitive effort; and (3) completion time falling significantly below the minimum acceptable threshold required to read and process the items. Consequently, 502 valid responses were retained for the final analysis, yielding an effective recovery rate of 74.37%.

The sample exhibited strong representative validity, with a gender distribution (45.22% male; 54.78% female) closely aligned with actual enrollment. Age distribution was dominated by the 26-30 age group (37.05%), consistent with adult distance education demographics. In terms of socio-occupational status, 57.57% were married, and 68.13% were unemployed. Academic majors included Computer Science (43.63%), Law (35.26%), and Administrative Management (21.12%). Notably, 45.62% of respondents utilized the learning platform daily, while only 6.38% reported weekly usage, indicating high platform engagement among the sampled participants. For the detailed demographic profile, please refer to Table 1 (Panel B).

4.2 Data Diagnostics, Common Method Bias, and Measurement Model

Prior to evaluating the measurement model, data screening was conducted. No missing values or multivariate outliers (assessed via Mahalanobis distance at $p<0.001$) were identified. Normality was confirmed as the maximum absolute skewness (0.181) and kurtosis (1.291) were well within the recommended thresholds of 3 and 10. Furthermore, to address potential common method bias (CMB), Harman's single-factor test was performed. The unrotated exploratory factor analysis revealed that the first principal component accounted for only 34.22% of the total variance, strictly below the 50% threshold. Thus, CMB is not a pervasive issue in this study. Additionally, the Variance Inflation Factor (VIF) was assessed to evaluate potential multicollinearity among the structural model's predictor constructs. The inner VIF values ranged from 1.223 to 1.391, which are well below the conservative threshold of 3.3, confirming that multicollinearity does not confound the structural parameter estimates.

Table 2: Confirmatory Factor Analysis (CFA), Composite Reliability (CR), and Average Variance Extracted (AVE) Results

Variable	Measurement Indicator	No. Of Item	Cronbach's Alpha	Factor Loading	CR	AVE
Academic Self efficacy (ASE)	(Kuo et al., 2021)	7	0.908	0.756-0.788	0.908	0.584
Sense of Belonging (SOB)	(Yi et al., 2024)	4	0.853	0.761-0.776	0.853	0.591
Information Quality (IQ)	(Chang, 2013)	4	0.859	0.729-0.804	0.859	0.604
Service Quality (SQ)	(Chang, 2013)	3	0.837	0.757-0.824	0.838	0.633
Cognitive Engagement (CE)	(Cheng, 2025a)	4	0.863	0.774-0.802	0.863	0.612
Emotional Engagement (EE)	(Yi et al., 2024)	4	0.863	0.784-0.796	0.863	0.612
Learning Persistence (LP)	(Cheng, 2024)	3	0.842	0.776-0.825	0.843	0.641

Note: CR = Composite Reliability, AVE = Average Variance Extracted

The reliability and validity of the measurement model were assessed using Confirmatory Factor Analysis (CFA), as presented in Table 2. The results indicate that factor loadings for all items ranged from 0.729 to 0.825, exceeding the 0.50 threshold (Hair et al., 2010). The Composite Reliability (CR) values ranged from 0.838 to 0.908, surpassing the recommended 0.70 (Hair et al., 2010). Furthermore, the Average Variance Extracted (AVE) values for all constructs were above 0.584, exceeding the 0.50 criterion. These indices collectively confirm robust convergent validity for the model.

Regarding reliability, the Cronbach's Alpha coefficients for all dimensions ranged from 0.837 to 0.908, significantly higher than the 0.70 benchmark (Hair et al., 2010), indicating excellent internal consistency. Overall, the measurement instrument demonstrates high stability and validity, satisfying the requirements for further structural model analysis.

Table 3: Goodness of Fit for Measurement Model

GOF Index	Criteria	Statistical Value
CMIN/DF (Hair et al., 2010)	<3	1.237
GFI (Hair et al., 2010)	≥0.90	0.989
AGFI (Hair et al., 2010)	≥0.80	0.926
RMSEA (Kline, 2023)	≤0.05	0.022
CFI (Hair et al., 2010)	≥0.90	0.989
NFI (Hair et al., 2010)	≥0.90	0.946
TLI (Hair et al., 2010)	≥0.90	0.989

Note: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

Table 3 summarizes the goodness-of-fit statistics for the measurement model. The empirical results indicate that the chi-square to degrees of freedom ratio (CMIN/DF) is 1.237, which is well below the threshold of 3. The RMSEA is 0.022, performing better than the stringent criterion of 0.05. Meanwhile, both GFI (0.989) and AGFI (0.926) exhibit excellent performance. Regarding incremental fit, the values for CFI, NFI, and TLI range from 0.946 to 0.989, significantly exceeding the recommended threshold of 0.90. In summary, all fit parameters align closely with the suggested standards, demonstrating an excellent fit between the observed data and the theoretical model, which supports further path analysis.

To rigorously assess discriminant validity, this study employed the Heterotrait-Monotrait (HTMT) ratio of correlations, a more stringent criterion that addresses the limitations of the traditional Fornell-Larcker approach in structural equation modeling. As presented in Table 4, the highest HTMT value is 0.570 (between LP and SOB), which is significantly below the stringent threshold of 0.85 (Henseler et al., 2015). This confirms the absence of multicollinearity and establishes that all seven dimensions are conceptually distinct and suitable for subsequent structural path analysis.

Table: 4 Discriminant Validity(HTMT Ratio)

Constructs	ASE	SOB	IQ	SQ	CE	EE	LP
ASE	-						
SOB	0.499	-					
IQ	0.433	0.454	-				
SQ	0.417	0.455	0.513	-			
CE	0.512	0.463	0.543	0.513	-		
EE	0.466	0.543	0.439	0.461	0.492	-	
LP	0.533	0.570	0.510	0.508	0.544	0.553	-

Note: All HTMT values are below the conservative threshold of 0.85, establishing strict discriminant validity.

4.3 Structural Equation Model (SEM)

Following the validation of the measurement model via CFA, this study employed Structural Equation Modeling (SEM) to perform path testing for the research hypotheses.

The goodness-of-fit for the structural model was evaluated prior to hypothesis testing (see Table 5). The statistical results demonstrate that all key indices fall within ideal ranges. Specifically, the CMIN/DF value is 2.394, meeting the criterion of being less than 3, while the RMSEA is 0.053, which is below the 0.08 threshold. Additionally, both GFI (0.876) and AGFI (0.853) exceed the 0.80 benchmark, indicating satisfactory model fit.

In addition to the global fit indices, the model's predictive accuracy and explanatory power were evaluated. The coefficient of determination (R^2) values for CE, EE, and LP were 0.316, 0.273, and 0.357, respectively. These results demonstrate moderate and satisfactory explanatory power, with the model accounting for 35.7% of the total variance in learning persistence through the hypothesized dual-path mediation.

Table 5 Goodness of Fit for Structural Model

GOF Index	Criteria	Statistical Value
CMIN/DF	<3(Hair et al., 2010)	2.394
GFI	≥0.80(Yi et al., 2024)	0.876
AGFI	≥0.80(Allen et al., 2018)	0.853
RMSEA	≤0.08(Hair et al., 2010)	0.053
CFI	≥0.90(Hair et al., 2010)	0.934
NFI	≥0.80(Hair et al., 2010)	0.892
TLI	≥0.90(Hair et al., 2010)	0.927

Note: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

The structural model was evaluated to test the predefined direct hypotheses (H1-H10). Standardized path coefficients (β), and the significance levels for each hypothesized relationship are summarized in Table 6. As shown, all ten structural paths received statistically significant support at the $p < 0.01$ level or higher.

Table 6: Direct Hypothesis Testing Results

Hypotheses	Path	Standardized Path Coefficient(β)	Tests Result
H1	CE <---ASE	0.305***	Supported
H2	EE <---ASE	0.242***	Supported
H3	CE <---SOB	0.182**	Supported
H4	EE <---SOB	0.371***	Supported
H5	CE <---IQ	0.338***	Supported
H6	EE <---IQ	0.173**	Supported
H7	CE <---SQ	0.275***	Supported
H8	EE <---SQ	0.215***	Supported
H9	LP<---CE	0.370***	Supported
H10	LP<---EE	0.383***	Supported

Note: *** = p < 0.001; ** = p < 0.01.

The structural model evaluation (Table 6) confirms all direct hypotheses. Regarding individual traits, both ASE and SOB significantly drive multidimensional engagement. Notably, SOB exhibits a significantly stronger effect on EE (β=0.371, p<0.001) than on CE (β=0.182, p<0.01), confirming its role as a primary emotional trigger. Conversely, ASE predominantly stimulates CE (β=0.305, p<0.001), suggesting that learners with higher self-efficacy are more likely to strategically deploy cognitive resources during their initial transition to the open learning environment.

4.5 Mediation Analysis and Effects Decomposition

To rigorously evaluate the mediating mechanisms and provide a comprehensive overview of the causal pathways in the S-O-R framework, a bootstrapping procedure with 5,000 resamples was conducted. This analysis decomposed the total effects of the stimuli on learning persistence into their direct and indirect components.

As specified in the theoretical framework, the model examines how the four independent variables (ASE, SOB, IQ, and SQ) ultimately influence learning persistence (LP) through the dual-path mediation of Cognitive Engagement (CE) and Emotional Engagement (EE). Utilizing the effect decomposition function, Table 7 provides a detailed presentation of the specific values for the direct, indirect, and total effects across all influence paths in this research.

Table 7: Direct, Indirect, and Total Effects of the Interconnection

Path	Direct Effect (β)	Indirect Effect (β)	Total Effect (β)
ASE-->LP	-	0.206***	0.206***
SOB-->LP	-	0.210***	0.210***
IQ--->LP	-	0.191***	0.191***
SQ--->LP	-	0.184***	0.184***

Path	Direct Effect (β)	Indirect Effect (β)	Total Effect (β)
CE--->LP	0.370***	-	0.370***
EE--->LP	0.383***	-	0.383***

Note: *** p < 0.001. R^2 for LP = 0.357.

The results confirm the significance of the hypothesized mediational mechanisms. The R^2 value for LP was 0.357, suggesting that ASE, SOB, IQ, and SQ collectively account for 35.7% of the total variance in learning persistence through the dual-path mediation of cognitive and emotional engagement. This underscores that the influence of both platform characteristics and individual traits is effectively channeled through the student's psychological and organismic states, validating the robustness of the extended S-O-R paradigm in the Open University context.

5. Discussion and Conclusion

5.1 Discussion

The empirical results provide robust evidence for the mechanisms driving learning persistence within the Open University context, validating the theoretical necessity of the Extended S-O-R framework.

5.1.1 The Dual-Track Stimulus Mechanism

A critical theoretical contribution of this study is the empirical validation of both internal and external stimuli in driving multidimensional engagement. The results confirm that pre-existing psychological schemas (ASE) and prior climate perceptions (SOB) are not merely outcomes, but function as potent "internal stimuli" (Shang & Lyv, 2024). Specifically, while Information Quality (an external stimulus) is the primary driver of cognitive processing (β=0.338), Sense of Belonging (an internal stimulus) exerts the strongest effect on emotional engagement (β=0.371). This supports recent IS research indicating that social interaction stimuli effectively initiate flow-like affective states (Hongsuchon et al., 2025). It suggests that in the physically isolated environment of distance education, a student's internalized sense of community acts as a necessary psychological baseline, filtering the external "digital weather" to mitigate isolation.

Furthermore, Academic Self-Efficacy predominantly drives cognitive engagement (β=0.305). This aligns with the subjective appraisal mechanism (Lucas et al., 2006), demonstrating that high self-efficacy acts as an internal force (Yang et al., 2022) that primes learners to deploy cognitive resources proactively when interacting with system features, rather than reacting passively to them.

5.1.2 Explaining the Dominance of Emotional Engagement

Addressing the relative impact of the organismic states, this research reveals that emotional engagement (β=0.383) exerts a more profound influence on persistence than cognitive engagement (β=0.370). This phenomenon highlights the "compound psychological effects" inherent in social and digital learning environments (Palamidovska-Sterjadovska et al., 2024). While cognitive engagement ensures task completion, it is the emotional resonance—triggered largely by the internal stimulus of belonging—that sustains the intrinsic motivation required to overcome temporal-spatial separation. Positive affect, as a significant correlate of approach behavior (Souki et al., 2026), plays a vital role in fostering long-term commitment in non-traditional higher education.

5.2 Conclusion

This study concludes that learning persistence among Open University undergraduates is governed by a dual-pathway mechanism integrating "Internal Trait Triggering" and "External System Enablement." The structural equation model confirms that both external system characteristics (IQ, SQ) and internal psychological schemas (ASE, SOB) act as simultaneous stimuli. Furthermore, the relationship between these dual-track stimuli and learning persistence is effectively channeled through the dual-pathway mechanism of cognitive and emotional engagement.

5.3 Recommendations

Based on the empirical findings, the following practical implications are proposed for Open University administrators.

First, concerning the activation of internal stimuli through affective design, platforms must prioritize interventions that trigger Sense of Belonging prior to academic tasks. This involves integrating synchronous peer-interaction tools, virtual onboarding communities, and humanized interface designs to establish a baseline social interaction stimulus (Hongsuchon et al., 2025).

Furthermore, in terms of optimizing external stimuli for cognitive load, to match the cognitive processing activated by ASE, digital resources (IQ) must be optimized for clarity. Utilizing micro-module content and knowledge graph visualizations can effectively reduce cognitive strain, supporting the external stimulus track.

Finally, to establish future-oriented support systems, given the significant impact of Service Quality, institutions should explore advanced, proactive support systems. Integrating 24/7 AI-tutors and predictive behavioral models could serve as continuous external stimuli that dynamically bolster students' psychological security.

5.4 Limitations and Further Study

This study acknowledges several limitations. First, the cross-sectional design captures a static snapshot of learner behavior; longitudinal designs are recommended to observe how internal stimuli evolve across an academic year. Second, the purposive sampling strategy (80-point threshold) may introduce selection bias toward highly engaged learners. Future studies should incorporate at-risk cohorts to validate the model's boundary conditions. Finally, while this model utilizes an extended S-O-R framework, future research should incorporate broader sociodemographic external stimuli, such as family-work-study conflict, to construct a more holistic predictive ecosystem.

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