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Learning Experience, Learning Behavior, and Major Retention Intention: Mediating and Moderating Pathways among Chinese Undergraduates

Mengyuan Lei

Institute of Higher Education, Tongji University, Shanghai, China

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Abstract— *Whether students are willing to choose their own major again is an important indicator of the quality of education. In China, most students enter their major through the national college entrance examination, so this issue is particularly important. This study examines whether learning experience (course experience, resource support, and academic advising) mediates the link between learning behavior and major retention intention, and whether learning behavior moderates each dimension. We investigated 4,765 undergraduates in a large public university in mainland China, and used structural equation modeling, bootstrap parallel mediation analysis, and moderation analysis. Learning behavior not only directly predicts retention intention, but also indirectly predicts retention intention. The three dimensions of experience account for 58.98% of the total effect, among which course experience is the strongest path. Learning behavior weakened the relationship between resource support and retention intention ($\beta = -0.12$, $p < .001$), but enhanced the role of academic advising ($\beta = 0.08$, $p < .05$). This "support mismatch" pattern suggests that the best effect can be achieved only when institutional support matches students' engagement level.*

Keywords— ***Learning Experience, Learning Behavior, Major Retention Intention, Support Mismatch, Structural Equation Modeling***

I. INTRODUCTION

Whether students are willing to choose their own major again is an important indicator of the quality of education and also reflects their commitment to future study and work (Tinto, 1993). This issue is particularly important in China. Most students are assigned to majors through the college entrance examination, and many know little about their majors before entering university.

Previous studies have focused on two types of factors. The first category is learning experience, that is, how students view their own courses, resources, and advising (Entwistle, 1991). The second category is learning behavior, that is, what students actually do in learning (Kuh et al., 2008). Both types of factors are related to academic persistence (Kahu, 2013; Tinto, 2017). However, few studies have investigated how the two work together, and even fewer studies have used large samples from Asia. Astin's (1993) I-E-O model provides a useful framework. This model relates the characteristics students bring, the environment they experience, and the final outcomes. One of its limitations is that it is often assumed that the environment has the same effect on every student, but recent studies have questioned this view (Crawford et al., 2024).

Based on the data of 4,765 undergraduates in China, this study answers two questions. First, does learning experience carry part of the influence of learning behavior on major retention intention? Second, does learning behavior change the strength of the relationship between each type of learning experience and retention intention? In short, we find that learning experience accounts for more than half of the effect; learning behavior weakens the value of resource support, but increases the value of academic advising.

1.1 Learning Experience and Major Retention Intention

Learning experience refers to students' perception of the learning environment, including course experience, resource support, and academic advising. Entwistle (1991) believes that it is students' perception of the environment that affects their learning, not the environment itself. Positive perception is related to stronger engagement, motivation, and persistence (Kahu, 2013).

Mosia et al. (2026) analyzed the records of 8,300 first-year students at a university in South Africa. Students who used academic advising services were more likely to stay in university and to progress. Stofile and Enwereji (2025) investigated 660 third-year students in South Africa. Academic support services such as tutoring and writing assistance were closely related to students' satisfaction ($r = .78$). Saeed and Mohamedali (2022) also found that a feedforward teaching approach improved students' performance, engagement, and retention. We propose:

> **H1:** Course experience, resource support, and academic advising are each positively correlated with major retention intention.

1.2 Learning Behavior, Learning Experience, and Retention Intention

Learning behavior includes class participation, self-study, and extracurricular academic activities (Kuh et al., 2008). Zhao and Kuh (2004) found that students who participated in learning communities were more engaged and more satisfied with college. Active students have more contact with teachers, courses, and services, so they may evaluate them more positively. Therefore, we expect:

> **H2:** Learning behavior is positively related to course experience, resource support, and academic advising.

Learning behavior can also predict academic persistence. Kuh et al. (2008) found that engagement in the first year is related to higher grades and a higher rate of returning to university in the second year. Tinto (1993) argues that students who are better integrated into academic life are more likely to stay. Therefore, active students may establish closer ties with their majors. We propose:

> **H3:** Learning behavior is positively related to major retention intention.

1.3 The Mediating Role of Learning Experience

Galve-González et al. (2024) studied 1,177 Spanish university students. They found that academic engagement linked social integration, course satisfaction, and expectations with the use of self-regulated learning strategies. Among the students who had considered dropping out, this mediation was full; among the students who intended to stay, it was partial. However, engagement and experience are likely to influence each other (Kahu, 2013). More engaged students may form a better view of courses, resources, and advisors, thus increasing their commitment to their majors. In terms of the I-E-O model, the perceived environment may transfer part of the influence of students' behavior to the outcome. So we propose:

> **H4:** Learning experience plays a mediating role between learning behavior and major retention intention.

1.4 The Moderating Role of Learning Behavior

Learning behavior may also change the strength of the relationship between each type of experience and retention intention. The evidence in this regard is inconsistent. Some studies have found that support is generally related to better student outcomes (Mosia et al., 2026; Stofile & Enwereji, 2025). Other studies show that not all support is equally useful. Crawford et al. (2024) surveyed 1,159,768 Australian students, and found that the overall educational experience and connection with other students predicted a sense of belonging more strongly than skill development and curriculum support. The value of support may also vary from student to student. Kuh et al. (2008) found that engagement has a compensatory effect, and historically underserved students benefit more from it. On the contrary, Mosia et al. (2026) found that academic advising was most helpful when students also performed well in orientation courses. This shows that academic advising and students' active efforts are complementary.

Person-environment fit theory helps to explain why the direction of moderation may differ (Edwards et al., 1998). When what the environment provides matches personal needs, the effect is the best; unmatched support may appear useless or even limiting. Highly engaged students may already be able to direct their own studies, so standardized resources such as fixed library services or general tutoring are of little help to them. Academic advising starts from students' own goals and can be adjusted, so it may be more suitable for them. So we put forward an exploratory hypothesis:

> **H5 (Exploratory):** Learning behavior moderates the relationship between learning experience and major retention intention, and the direction of moderation may differ across the three dimensions.

II. MATERIALS AND METHODS

2.1 Participants and Procedure

The participants were 4,765 undergraduates from a large public research university in mainland China, all of whom

volunteered to participate. The sample included 3,018 males (63.3%) and 1,747 females (36.7%). By year of study, there were 1,302 freshmen (27.3%), 1,520 sophomores (31.9%), 1,158 juniors (24.3%), 90 non-graduating seniors (1.9%), and 695 graduating students (14.6%). This study adopted convenience sampling. After the approval of the university administration, the researchers recruited students through flyers and class announcements, and students who were interested in participating received a secure online questionnaire link and an informed consent form.

All participants signed the written informed consent online. This study was approved by the university's ethics review committee before data collection (approval number withheld for blind review).

2.2 Measures

Learning experience. Ten items were adapted from Entwistle's (1991) framework on students' perception of the learning environment, including course experience (4 items, $\alpha = 0.78$), resource support (3 items, $\alpha = 0.80$), and academic advising (3 items, $\alpha = 0.75$). The items are rated on a 5-point scale (1 = very easy or sufficient, 5 = very difficult or insufficient). We reverse-scored the items, so that the higher the score, the better the experience.

Learning behavior. Five items were adapted from Amhag and Jakobsson (2009) to measure class participation, self-study time, and extracurricular academic activities (5-point scale, $\alpha = 0.82$).

Major retention intention. This study uses one item: "If I could choose again, I would still choose this major" (1 to 5 points). Bergkvist and Rossiter (2007) found that when the construct is concrete and simple, the predictive power of a single-item measure can be equivalent to that of a multi-item scale. Wanous et al. (1997) obtained similar results for overall job satisfaction. This item directly expresses a clear and specific intention. However, Diamantopoulos et al. (2012) cautioned that single items can only be equivalent to multi-item scales under certain conditions. Therefore, we are cautious in interpreting this measure.

2.3 Data Analysis

We used SPSS 26.0 and AMOS 26.0 to calculate descriptive statistics and correlations, and compared students of different genders and years with t-tests and one-way ANOVA. We tested multicollinearity, homoscedasticity, and independence of errors (Kline, 2015). We used exploratory and confirmatory factor analysis to test construct validity and reliability (Hair et al., 2010). We used Harman's single-factor test and a common latent factor model to evaluate common method bias (Podsakoff et al., 2012). Model fit was judged by χ^2, CFI, TLI, and RMSEA (Hu & Bentler, 1999; Tseng & Schmitt, 2008). CFI and TLI close to or higher than .95, and RMSEA close to or lower than .06, indicate good fit. Because χ^2 is very sensitive to large samples, we did not judge by it alone (Kline, 2015).

Then, we used the PROCESS macro for SPSS (Model 4; Hayes, 2022) to test the parallel mediation model. Learning behavior is the predictor, the three experience dimensions are parallel mediators, and retention intention is the outcome variable. The indirect effects were tested with 5,000 bootstrap samples. If the 95% confidence interval does not contain zero, the indirect effect is significant. Finally, we used mean-centered scores to construct the interaction terms between learning behavior and each experience dimension to test the moderating effect. Since learning behavior is also the predictor in the mediation model, this test can explain whether the influence of each mediator on the outcome depends on the predictor (Hayes, 2022).

2.4 Data Availability and Use of Generative AI

Because the data contain student information, they will not be made public. Readers can reasonably apply to the corresponding author for the de-identified data. In this study, generative artificial intelligence tools were used only for language editing and formatting, and the authors are responsible for all the contents.

III. RESULTS

3.1 Descriptive Statistics and Preliminary Analyses

Table 1 lists the mean, standard deviation, and correlation coefficient of each variable. All correlations are positive and significant. Learning behavior is related to resource support ($r = .40$) and retention intention ($r = .42$). Resource support is highly correlated with academic advising ($r = .79$). All the mean values are lower than the midpoint of the scale (3), which shows that many students' evaluation of their learning experience and major is only moderate.

The data meet the main statistical assumptions. The VIF values range from 1.01 to 2.97, which is far below the commonly used cut-off of 10 (Hair et al., 2010). The Breusch-Pagan test was not significant ($p > .05$), and Durbin-Watson values ranged from 1.5 to 2.5. The absolute value of skewness is less than 2 and that of kurtosis is less than 7. There are no signifsicant outliers, and missing values are less than 5%, which were handled with the full information maximum likelihood method.

3.2 Measurement Model and Common Method Bias

The χ^2 test of the measurement model was significant ($p < .05$). However, other indices show a good fit: CFI = 0.97,

TLI = 0.96, RMSEA = 0.04, 90% CI [0.03, 0.05]. All factor loadings were significant ($p < .01$). The composite reliability is higher than 0.70, and the average variance extracted is higher than 0.50. In Harman's test, the first factor explains 28% of the variance, which is lower than the 50% threshold. After adding a common latent factor, the model fit did not improve. Therefore, common method bias is unlikely to pose a problem.

3.3 Path Analysis

The structural model also fits well (CFI = 0.97, TLI = 0.95, RMSEA = 0.04, 90% CI [0.02, 0.06]). Table 2 lists the path coefficients.

Table 1: Descriptive Statistics and Correlations (N = 4,765)

Variable	*M*	*SD*	1	2	3	4
1. Course experience	2.04	0.74				
2. Resource support	1.76	0.80	.64***			
3. Academic advising	1.68	0.78	.62***	.79***		
4. Learning behavior	2.54	0.84	.60***	.40***	.40***	
5. Retention intention	2.18	0.93	.51***	.49***	.48***	.42***

Note. ***p < .001.

Independent samples t-tests show that there are gender differences in course experience (t = 4.75), resource support (t = 6.01), and academic advising (t = 7.93), all $p < .001$. One-way ANOVA shows that there are year differences in course experience (F = 5.36), resource support (F = 9.83), academic advising (F = 16.47), and retention intention (F = 7.22), all $p < .001$. There is no significant year difference in learning behavior.Gender differences were also found in learning behavior (t = 1.95, $p < .001$) and retention intention (t = 0.98, $p < .001$).

Table 2: Path Coefficients of the Parallel Mediation Model

Path	*β*	*SE*	*p*
Learning behavior → Course experience	0.53	0.01	< .001
Learning behavior → Resource support	0.38	0.01	< .001
Learning behavior → Academic advising	0.37	0.01	< .001
Course experience → Retention intention	0.26	0.02	< .001
Resource support → Retention intention	0.20	0.02	< .001
Academic advising → Retention intention	0.17	0.02	< .001
Learning behavior → Retention intention (direct)	0.19	0.02	< .001

Note. β is the standardized coefficient. The paths to retention intention control for other predictors. The four predictors explain 43% of the variance in retention intention.

Learning behavior positively predicted course experience (B = 0.53), resource support (B = 0.38), and academic advising (B = 0.37), all $p < .001$, and H2 was supported. After controlling for learning behavior, course experience (B = 0.26), resource support (B = 0.20), and academic advising (B = 0.17) all predicted retention intention, all $p < .001$, and H1 was supported. Learning behavior still has a direct effect on retention intention (B = 0.19, $p < .001$), and H3 is supported.

3.4 Mediation Analysis

As shown in Table 3, the total indirect effect is 0.2777, 95% CI [0.2520, 0.3034], accounting for 58.98% of the total effect. In standardized terms, it is about 0.25. As the direct effect is still significant, the mediation is partial, and H4 is supported. Course experience accounts for the largest share (28.82%), followed by resource support (16.33%) and academic advising (13.83%). Fig. 1 shows the model.

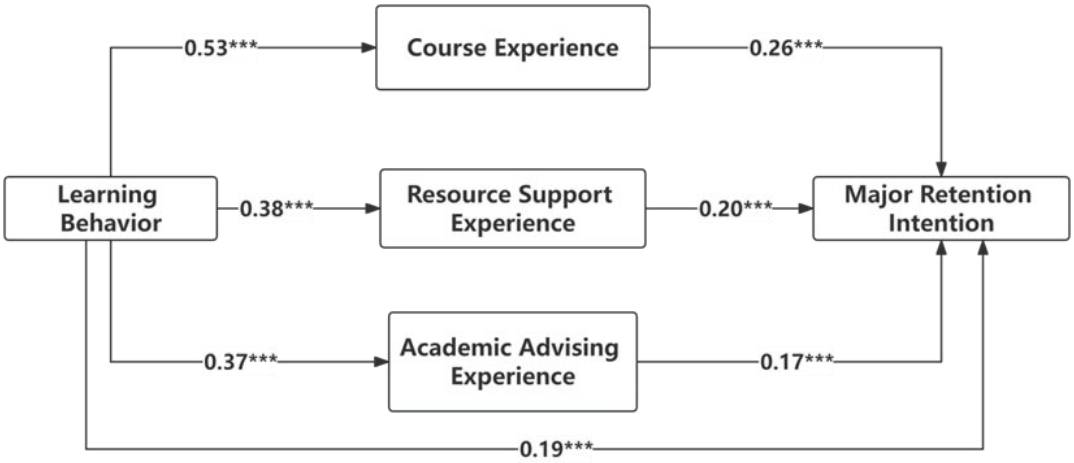

Fig.1. Parallel mediation model linking learning behavior to major retention intention through three dimensions of learning experience

Note. The coefficients are standardized coefficients. ***p < .001.

Table 3: Total, Direct, and Indirect Effects of Learning Behavior on Major Retention Intention

Effect	Estimate	*SE*	LLCI	ULCI	% of Total
Total effect	0.4708	0.0144	0.4425	0.4991	100.00
Direct effect	0.1931	0.0163	0.1612	0.2250	41.02
Total indirect effect	0.2777	0.0130	0.2520	0.3034	58.98
Via course experience	0.1357	0.0142	0.1086	0.1642	28.82
Via resource support	0.0769	0.0114	0.0547	0.0992	16.33
Via academic advising	0.0651	0.0110	0.0440	0.0869	13.83

Note. LLCI and ULCI are the lower and upper limits of the 95% confidence interval, respectively. The intervals of the total effect and direct effect are normal-theory intervals, and the intervals of the indirect effects are percentile bootstrap intervals based on 5,000 samples.

3.5 Moderation Analysis

The moderation model was significant ($R = 0.76$, $R^2 = 0.583$., $F = 271.30$, $p < .001$). Table 4 lists the interaction terms.

Table 4: Moderating Effects of Learning Behavior

Interaction term	*β*	*t*	*p*
Course experience × Learning behavior	0.02	0.95	n.s.
Resource support × Learning behavior	-0.12	-3.97	< .001
Academic advising × Learning behavior	0.08	2.59	< .05

Note. β is the standardized coefficient. n.s. = not significant.

The interaction of course experience is not significant. The interaction term of resource support is negative (β = -0.12, p < .001), which shows that the relationship between resource support and retention intention is weaker for students who are more active in learning. The interaction term of academic advising is positive (β = 0.08, p < .05), which shows that academic advising has a stronger connection with retention intention for students who are more active

in learning. H5 is partially supported because the direction of moderation varies from dimension to dimension. All interaction effects are small in size.

IV. DISCUSSION

4.1 Main Findings

The results support H1 to H4, and partially support H5. First, all three dimensions of experience are positively related to retention intention. This is consistent with the findings of Mosia et al. (2026) and Stofile and Enwereji (2025), who associate academic advising and academic support with retention and satisfaction. This study extends this evidence to undergraduates in China, and focuses on the willingness to stay in the major, not just in the university. The mean of retention intention is low (M = 2.18), which also shows the importance of this issue in China.

Second, learning behavior not only directly predicts retention intention, but also indirectly predicts retention intention through learning experience. Course experience is the strongest path. Active students spend more time on courses, so a good course experience may make them feel that this major is worth keeping. This result also complements the research of Galve-González et al. (2024). They placed engagement between students' views of their studies and their learning strategies, and we find that experience can also sit between behavior and outcomes. Taken together, the two studies show that there may be a two-way relationship between them. Awuonda (2025) also found in a sample of 201 graduate students that advisor quality is partly related to learning outcomes through academic motivation.

4.2 The Support Mismatch Pattern

We call the most noteworthy finding a "support mismatch" pattern. Learning behavior weakens the role of resource support, but enhances the role of academic advising.

Person-environment fit theory provides the first explanation (Edwards et al., 1998). Highly engaged students may rely less on formal resources and more on self-directed learning or peer learning. Standardized resources may not meet their needs, so they contribute less to their major commitment. In contrast, academic advising starts from students' own problems and goals. More engaged students may be better at asking useful questions and acting on suggestions.

Self-determination theory provides a second explanation (Deci & Ryan, 2000). Students need to feel autonomous, so for students with strong autonomy, fixed standardized services may feel more like external control. This may be an "over-support" effect. Individualized academic advising is more likely to support their own choices, and Awuonda (2025) also emphasizes the value of autonomy-supportive academic advising.

The third explanation is compensation. Less engaged students may rely more on institutional resources, so these resources are more important to their major commitment. This is consistent with the compensatory effect reported by Kuh et al. (2008). The cross-sectional data of this study cannot distinguish these explanations. Selection effects may also exist, because students with strong motivation may not only be more engaged, but also seek good advising. Mosia et al. (2026) gave the same warning about their results.

4.3 Theoretical Contributions

This study has three theoretical contributions. Firstly, it illustrates the internal process of Astin's (1993) I-E-O model. Students' behavior affects how they perceive the environment, and the perceived environment transmits most of the influence to the outcome. Second, it identifies a boundary condition. The relationship between environment and outcomes depends on whether the type of support matches students' engagement level. According to person-environment fit theory, standardized resources create a needs-supplies mismatch for highly engaged students (Edwards et al., 1998). Thirdly, it supports Kahu's (2013) view that engagement is formed in the interaction between students and institutions. Learning behavior is not only a conduit that opens this path, but also a filter that changes how much each type of support matters.

V. CONCLUSION

5.1 Conclusions and Implications

Among the 4,765 undergraduates in China, learning behavior not only directly predicts major retention intention, but also indirectly predicts it through three dimensions of learning experience, and the latter accounts for nearly 60% of the total effect. Learning behavior moderates the effects of resource support and academic advising in opposite directions.

Three practical implications can be drawn from this. First, universities should improve the course experience, because it is the strongest path. Clear course objectives, useful feedback, and links between courses and careers may help students see the value of their major. Second, universities should adjust their support methods according to students' participation while ensuring that basic resources are generally open. Students with low participation can get more active help, while students with high participation need more flexible and advanced resources. Because the adjustment effect is not great, the focus should be on

optimizing the support mode rather than reducing resources. Thirdly, academic advising should continue to serve as personalized support for all students, helping them cope with learning difficulties and strengthening contact with teachers and students. For students with low participation, schools should also guide them to use academic advising more effectively.

5.2 Limitations and Future Research

There are still some limitations in this study. First, the data come from one research university, and future research should include comprehensive universities, normal universities, and vocational colleges. Second, all data are self-reported, and there may be social desirability bias. Thirdly, this study uses a cross-sectional design, and it is impossible to confirm the causal direction. Learning experience may also affect learning behavior in turn, which requires a longitudinal design to test both directions. Fourthly, measuring retention intention with only one item cannot reflect all its complexity (Diamantopoulos et al., 2012). Fifth, resource support and academic advising are highly correlated (r = .79), and their respective effects should be interpreted carefully. Future studies should also report simple slopes.

REFERENCES

[1] Amhag, L., & Jakobsson, A. (2009). Collaborative learning as a collective competence when students use the potential of meaning in asynchronous dialogues. *Computers & Education, 52*(3), 656-667. https://doi.org/10.1016/j.compedu.2008.11.012

[2] Astin, A. W. (1993). *What matters in college? Four critical years revisited*. Jossey-Bass.

[3] Awuonda, K. W. (2025). *Conceptualization of proactive academic advisement framework: A latent variable structural equation modeling approach* [Doctoral dissertation, Texas Tech University]. Texas Tech University Libraries.

[4] Bergkvist, L., & Rossiter, J. R. (2007). The predictive validity of multiple-item versus single-item measures of the same constructs. *Journal of Marketing Research, 44*(2), 175-184. https://doi.org/10.1509/jmkr.44.2.175

[5] Crawford, J., Allen, K.-A., Sanders, T., Baumeister, R., Parker, P., Saunders, C., & Tice, D. (2024). Sense of belonging in higher education students: An Australian longitudinal study from 2013 to 2019. *Studies in Higher Education, 49*(3), 395-409. https://doi.org/10.1080/03075079.2023.2238006

[6] Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry, 11*(4), 227-268. https://doi.org/10.1207/S15327965PLI1104_01

[7] Diamantopoulos, A., Sarstedt, M., Fuchs, C., Wilczynski, P., & Kaiser, S. (2012). Guidelines for choosing between multi-item and single-item scales for construct measurement: A predictive validity perspective. *Journal of the Academy of Marketing Science, 40*(3), 434-449. https://doi.org/10.1007/s11747-011-0300-3

[8] Edwards, J. R., Caplan, R. D., & Harrison, R. V. (1998). Person-environment fit theory: Conceptual foundations, empirical evidence, and directions for future research. In C. L. Cooper (Ed.), *Theories of organizational stress* (pp. 28-67). Oxford University Press. https://doi.org/10.1093/oso/9780198522799.003.0003

[9] Entwistle, N. J. (1991). Approaches to learning and perceptions of the learning environment. *Higher Education, 22*(3), 201-204. https://doi.org/10.1007/BF00132287

[10] Galve-González, C., Bernardo, A. B., & Núñez, J. C. (2024). Academic pathways: The role of engagement as a mediator in the decision to drop out or stay at university. *Revista de Psicodidáctica (English Edition), 29*(2), 130-138. https://doi.org/10.1016/j.psicoe.2024.05.001

[11] Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Pearson Prentice Hall.

[12] Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (3rd ed.). Guilford Press.

[13] 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. https://doi.org/10.1080/10705519909540118

[14] Kahu, E. R. (2013). Framing student engagement in higher education. *Studies in Higher Education, 38*(5), 758-773. https://doi.org/10.1080/03075079.2011.598505

[15] Kline, R. B. (2015). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

[16] Kuh, G. D., Cruce, T. M., Shoup, R., Kinzie, J., & Gonyea, R. M. (2008). Unmasking the effects of student engagement on first-year college grades and persistence. *The Journal of Higher Education, 79*(5), 540-563. https://doi.org/10.1353/jhe.0.0019

[17] Mosia, M., Sekonyela, L., Egara, F. O., Nimy, E., Mabokgole, I. M., & Nannim, F. A. (2026). Bayesian hierarchical modelling of academic orientation and advising effects on student retention and progression: Multi-cohort evidence. *PLoS ONE, 21*(3), e0345001. https://doi.org/10.1371/journal.pone.0345001

[18] Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology, 63*, 539-569. https://doi.org/10.1146/annurev-psych-120710-100452

[19] Saeed, N., & Mohamedali, F. (2022). A study to evaluate students' performance, engagement, and progression in higher education based on feedforward teaching approach. *Education Sciences, 12*(1), 56. https://doi.org/10.3390/educsci12010056

[20] Stofile, R., & Enwereji, P. C. (2025). Investigating the impact of institutional support services on student retention in a university in the Eastern Cape Province of South Africa.

Journal for Educators, Teachers and Trainers, 16(6), 174-191. https://doi.org/10.48047/jett.2025.16.06.07

[21] Tinto, V. (1993). *Leaving college: Rethinking the causes and cures of student attrition* (2nd ed.). University of Chicago Press.

[22] Tinto, V. (2017). Reflections on student persistence. *Student Success, 8*(2), 1-8. https://doi.org/10.5204/ssj.v8i2.376

[23] Tseng, W.-T., & Schmitt, N. (2008). Toward a model of motivated vocabulary learning: A structural equation modeling approach. *Language Learning, 58*(2), 357-400.

[24] Wanous, J. P., Reichers, A. E., & Hudy, M. J. (1997). Overall job satisfaction: How good are single-item measures? *Journal of Applied Psychology, 82*(2), 247-252. https://doi.org/10.1037/0021-9010.82.2.247

[25] Zhao, C.-M., & Kuh, G. D. (2004). Adding value: Learning communities and student engagement. *Research in Higher Education, 45*(2), 115-138. https://doi.org/10.1023/B:RIHE.0000015692.88534.de