Journal of International Conference Proceedings (JICP)
Vol. 8 No. 3, pp.27-39, December, 2025
E-ISSN: 2621-993X P-ISSN: 2622-0989
https://ejournal.aibpmjournals.com/index.php/JICP/index

Optimizing Human Capital Investment: VARK Learning Styles to Reduce Student Educational Costs

Lisa Gresti Sella Damanik[1]*, Xenia Irene Sandy Landjang[1]
[1]Management Study Program, Faculty of Economics and Business, Universitas Cenderawasih
Jl. Kamp Wolker Yabansai, Jayapura, Papua 99351, Indonesia
*Corresponding Email: lisa.damanik@feb.uncen.ac.id

ARTICLE INFORMATION

Publication information

Research article

HOW TO CITE
Damanik, L. G. S., & Landjang, X. I. S. (2025). Optimizing human capital investment: VARK learning styles to reduce student educational costs. *Journal of International Conference Proceedings, 8*(3), 27-39.

DOI:
https://doi.org/10.32535/jicp.v8i3.4194

Received: 27 September 2025
Accepted: 28 Oktober 2025
Published: 4 Desember 2025

ABSTRACT

The rising cost of higher education is a growing concern, particularly in regions with limited resources such as Papua, Indonesia, where academic challenges and extended study durations increase financial burden. This study examines the influence of VARK (Visual, Auditory, Read/Write, Kinesthetic) learning style identification and learning environment optimization on student educational cost reduction, with academic performance as a mediating variable. The sample consisted of 180 management students at Universitas Cenderawasih, with 125 respondents selected using Slovin's formula. Data were collected through structured questionnaires and analyzed using PLS-SEM (SmartPLS 3). The results indicate that learning style identification significantly improves academic performance ($\beta = 0.421$; $p < 0.001$) and reduces educational costs ($\beta = 0.255$; $p = 0.007$). Learning environment optimization also positively affects academic performance ($\beta = 0.413$; $p < 0.001$) and cost reduction ($\beta = 0.234$; $p = 0.024$). Academic performance strongly influences cost reduction ($\beta = 0.380$; $p = 0.002$) and mediates the effects of X1 → Z ($\beta = 0.160$; $p = 0.010$) and X2 → Z ($\beta = 0.157$; $p = 0.006$). The model demonstrates moderate explanatory power ($R^2 = 0.539$ for Academic Performance; $R^2 = 0.569$ for Student Educational Costs). The findings highlight the importance of personalized learning and optimized environments in reducing financial burden.

Keywords: Academic Performance; Educational Costs; Learning Environment Optimization; VARK Learning Styles

INTRODUCTION

The rising cost of higher education has become a global concern and is particularly critical in Indonesia, especially in the Papua region, where socioeconomic disparities and limited academic resources frequently contribute to delayed graduation. Academic performance is a major determinant of educational cost efficiency, as low achievement often results in course repetition and prolonged study duration. Identifying students' preferred learning approaches through the VARK model (Visual, Auditory, Read or Write, Kinesthetic) has been shown to improve comprehension, retention, and academic achievement, while mismatched learning strategies can reduce motivation and increase the risk of academic failure. The quality of the learning environment, including facilities, instructional resources, and social and psychological academic climate, also plays an important role in shaping student engagement, persistence, self confidence, and performance, which ultimately influences study length and associated educational costs. In many higher education systems, students who lack appropriate learning support frequently experience academic anxiety and reduced satisfaction, which can further increase the financial burden on families and institutions.

Although previous research has examined learning styles and learning environments individually, limited empirical evidence has explored their combined influence on academic performance and educational cost reduction. There remains a need to better understand how learning style alignment and supportive environments work together to create more effective learning experiences within university programs. To address this gap, the present study investigates the joint effects of VARK learning style identification and learning environment optimization on academic performance, with the reduction of student educational costs as the primary outcome. The findings are expected to provide important insights for educators and policymakers in designing more efficient learning systems aimed at improving academic outcomes and minimizing financial pressures. The implications extend to curriculum developers, academic advisors, and institutional leaders who seek evidence based strategies to enhance learning quality, reduce dropout rates, and promote equitable access to education for diverse student populations.

LITERATURE REVIEW

VARK Learning Style

Learning styles based on the VARK Model remain widely applied in higher education, with evidence demonstrating improved outcomes when instructional methods align with students' learning preferences, particularly among visual and kinesthetic learners (El-Saftawy et al., 2024; Lee, 2025). Multimodal learners also tend to achieve better academic results than unimodal peers (Noor & Ramly, 2023). However, limited studies directly examine the relationship between VARK alignment and educational cost efficiency, which the present study seeks to address. Additional research highlights that students who clearly understand their learning preferences are more confident and participate more actively in coursework, enabling more efficient mastery of concepts. Improved engagement may help reduce academic struggles that contribute to repeated subjects and increased educational expenses, reinforcing the importance of structured identification of learning styles across diverse student groups.

Learning Environment Optimization

A conducive learning environment that includes physical, psychological, and social elements has been associated with persistence and higher academic achievement. Adequate facilities, peer support, and access to digital learning resources reduce barriers and foster engagement (Rusticus et al., 2023; Mulyawan & Christanti, 2022). Broader infrastructure components such as electricity and internet reliability also influence learning effectiveness and student productivity, as observed across Southeast Asia. Although previous studies highlight these outcomes, few have investigated the relationship between learning environment quality and educational cost efficiency, which this research explores. Furthermore, a well-structured learning environment promotes consistency in learning activities and reduces disruptions that may lead to missed learning opportunities. The establishment of collaborative spaces and supportive academic communities also strengthens motivation and reduces dropout risks, resulting in improved academic continuity and lower educational costs.

Academic Performance

Academic performance, commonly measured through GPA, reflects the influence of learning preferences, motivation, and academic support. Internal factors such as self-efficacy and external components such as teaching quality jointly shape academic performance (Han, 2023). Poor performance often extends study duration and increases educational expenses (Marlina et al., 2021; Falch et al, 2022), while stronger achievement reduces delays and associated costs. Although this relationship is well established, the financial implications remain underexplored. This study addresses that gap by examining performance both as a direct outcome and as a mediator of cost reduction. Academic performance serves as a key predictor of student progression, influencing scholarship eligibility, academic recognition, and opportunities for career development. Improving academic outcomes contributes not only to personal achievement but also to institutional productivity and policy planning aimed at reducing systemic inefficiencies in the education sector.

Student Educational Cost Reduction

Student costs include tuition, living expenses, and opportunity costs resulting from delayed graduation. Increasing global tuition trends underscore the urgency for educational efficiency (College Board, 2024; World Bank, 2023). From a human capital perspective, timely completion improves education returns, while delays reduce them. Pedagogical strategies aligned with VARK preferences and strengthened learning environments help minimize course repetition and shorten study duration, thereby lowering expenses (Amir et al., 2023). Financial literacy further contributes to efficiency, as financially knowledgeable students are better able to manage academic spending (Kee et al., 2025). Therefore, cost reduction depends on both academic and behavioral components. Reducing educational cost burdens is also associated with improved access to higher education, allowing students from disadvantaged backgrounds to complete studies without excessive financial strain. Institutional strategies that integrate academic support services, technology investment, and transparent cost management demonstrate potential to increase completion rates and improve long-term financial outcomes for students.

Hypotheses Development

VARK Learning Style Identification and Academic Performance

Prior studies indicate that tailoring instruction to students' preferred learning styles enhances comprehension and academic achievement. The VARK model is widely used to identify these preferences and support differentiated instruction. Evidence suggests that visual and kinesthetic learners benefit significantly from aligned strategies (El-Saftawy et al., 2024), and similar improvements have been reported in professional education contexts (Lee, 2025). When teaching methods correspond to learner characteristics, students demonstrate greater engagement, motivation, and confidence in understanding course materials. These improvements lead to more effective knowledge absorption and encourage consistent academic effort, which strengthens performance outcomes. Based on this foundation, the first hypothesis is proposed as follows:

H1: VARK learning style identification positively influences academic performance.

Learning Environment Optimization and Academic Performance
A supportive learning environment, which includes adequate facilities, digital access, and positive classroom dynamics, has been associated with greater persistence and stronger academic results. Rusticus et al. (2023) demonstrated that perceived academic support correlates with improved performance, while Mulyawan & Christanti (2022) showed that optimized physical and digital environments foster student engagement. Blended learning environments that combine traditional and technology-based formats have been shown to sustain achievement levels across diverse conditions (Lusa et al., 2022; Kobicheva et al., 2022). An environment that minimizes distractions and builds learning communities can increase productivity and reduce academic fatigue. Therefore, the second hypothesis is proposed as:

H2: Learning environment optimization positively influences academic performance.

Academic Performance and Student Educational Cost Reduction
Academic performance reflects student achievement and contributes to educational efficiency. High-achieving students are less likely to repeat courses or extend their study periods, thereby reducing financial burdens, whereas poor outcomes often increase cumulative expenses (Marlina et al., 2021; Falch et al, 2022). Strong academic performance also improves access to scholarships and reduces the opportunity costs associated with delayed workforce entry. Efficient performance shortens program duration and minimizes extra fees linked to repeated subjects and extended tuition periods. Therefore, academic achievement must be viewed as a strategic mechanism for optimizing educational expenditure. Thus:

H3: Academic performance positively influences student educational cost reduction.

VARK Learning Style Identification, Academic Performance, and Cost Reduction
Recognition of VARK learning styles supports instructional strategies that enhance comprehension, which minimizes course repetition and delays, the primary contributors to rising educational expenses. Empirical evidence links learning style alignment with both performance and efficiency (Noor & Ramly, 2023; El-Saftawy et al., 2024), suggesting the mediating role of performance. Similar findings in health and management settings reinforce these connections (Mohsenipouya et al., 2024; Mozaffari et al., 2020). When teaching aligns with learning preferences, students learn more efficiently and avoid costly academic setbacks. Therefore, academic performance mediates the relationship between learning style identification and educational cost reduction.

H4: Academic performance mediates the relationship between VARK learning style identification and student educational cost reduction.

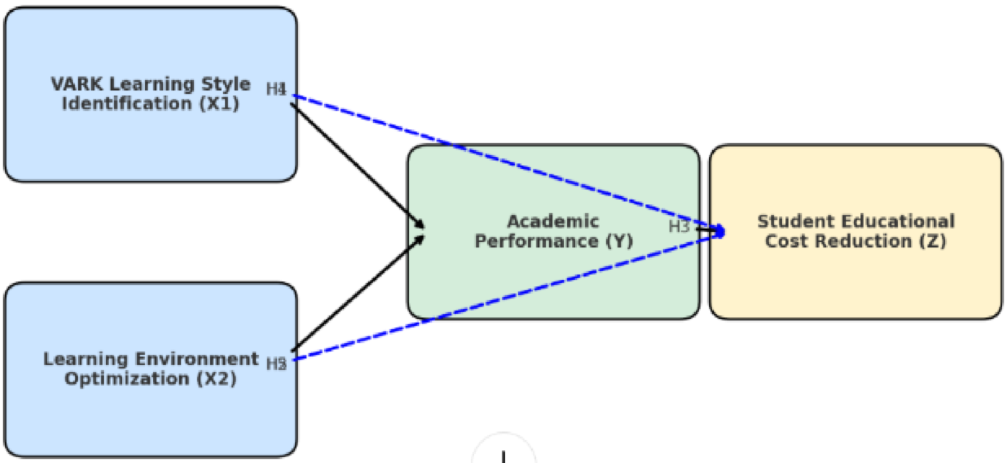
Learning Environment Optimization, Academic Performance, and Cost Reduction
Optimized learning environments enhance motivation and persistence, reducing inefficiencies in study completion. Research confirms that supportive academic conditions improve learning effectiveness (Rusticus et al., 2023; Mulyawan & Christanti, 2022), while weaker performance increases overall educational expenses (Falch et al, 2022). Additional studies suggest that digital learning access reduces costs by minimizing resource needs and increasing flexibility (Alenezi, 2023; Isaeva et al., 2025). Improved classroom infrastructure, academic support structures, and well-designed

academic systems increase completion rates and support financial sustainability. Therefore:

H5: Academic performance mediates the relationship between learning environment optimization and student educational cost reduction.

Conceptual Framework
The study framework model is depicted in Figure 1.

Figure 1. Research Framework



RESEARCH METHOD

Research Approach and Design
This study employed a quantitative research approach with a causal design to examine the relationships among VARK learning style identification, learning environment optimization, academic performance, and student educational cost reduction. The design enables the evaluation of direct and mediating effects among the study variables in accordance with the research hypotheses.

Sampling
The study population consisted of 180 undergraduate students enrolled in the Management program at Universitas Cenderawasih during the 2024/2025 academic year, with each student serving as the unit of analysis. A purposive sampling technique was applied to select respondents who had completed at least two semesters, ensuring sufficient exposure to the learning process and institutional environment. Based on Slovin's formula, the required minimum sample size was calculated to be 125 participants, which formed the dataset for this study.

Data Collection
Primary data were collected using an online questionnaire employing a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). The instrument was distributed through institutional communication channels to ensure accessibility and response accuracy. A pilot test involving 30 students was conducted to evaluate clarity, wording, and initial reliability prior to full-scale distribution.

Measures

All study variables were measured using validated instruments adapted from previous research. VARK learning style identification (X1) was assessed based on Fleming's (2006) classification of visual, auditory, read or write, and kinesthetic learning styles, commonly applied in higher education settings (Lee et al., 2024; El-Saftawy et al., 2024). Learning environment optimization (X2) included dimensions of facilities, instructional support, and social interaction according to Rusticus et al. (2023) and Mulyawan & Christanti (2022). Academic performance (Y) was measured using self-reported GPA and perceived learning outcomes (Han, 2023). Student educational cost reduction (Z) reflected reduced course repetition, shorter study duration, and lower indirect educational expenses (World Bank, 2023; Amir et al., 2023). Reliability and validity were tested using Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE).

Data Analysis

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 3 software, selected for its suitability in predictive modeling and its robustness in handling complex relationships and non-normal data distribution. The analysis procedure assessed both the measurement model and the structural model, with significance testing conducted using a bootstrapping procedure with 5,000 resamples.

RESULTS

The results of the study are presented in several stages, including descriptive statistics, measurement model assessment (reliability and validity), and structural model assessment.

Table 1. Descriptive Statistics (N = 125)

Construct	Min	Max	Mean	SD
Learning Style Identification (X1)	3.00	5.00	4.22	0.78
Learning Environment Optimization (X2)	3.00	5.00	4.20	0.78
Academic Performance (Y)	3.00	5.00	3.76	0.74
Student Educational Costs (Z)	3.00	5.00	4.12	0.73

Note. M = Mean, SD = Standard Deviation.
Source: Processed Data (2025)

Table 1 shows that the mean values of the four constructs range from 3.76 to 4.22 on a five-point Likert scale, indicating generally positive perceptions among respondents. Learning Style Identification (X1) recorded the highest mean (M = 4.22, SD = 0.78), followed by Learning Environment Optimization (X2) (M = 4.20, SD = 0.78). Student Educational Costs (Z) showed the lowest mean (M = 3.76, SD = 0.74), though still categorized as high, while Academic Performance (Y) obtained a mean score of 4.12 (SD = 0.73). The relatively small standard deviations (ranging from 0.73 to 0.78) indicate a low degree of variance in participants' responses, suggesting homogeneity within the dataset and supporting its suitability for subsequent hypothesis testing.

Table 2. Outer Loadings of Measurement Model

Indicator	Loading			
X1_01	0.827			
X1_02	0.829			
X1_03	0.824			
X1_04	0.849			
X2_01		0.839		

X2_02		0.816		
X2_03		0.810		
X2_04		0.832		
X2_05		0.836		
Y_01			0.855	
Y_02			0.742	
Y_03			0.836	
Y_04			0.795	
Y_05			0.776	
Y_06			0.794	
Z_01				0.774
Z_02				0.807
Z_03				0.796
Z_04				0.862
Z_05				0.797

Source: Processed Data (2025)

As presented in Table 2, the loading scores for all four constructs are greater than the cutoff value of 0.70 (Hair et al., 2019), ranging between 0.742 and 0.862. These findings verify that each indicator accurately represents its construct and support the robustness of the measurement model for subsequent validity and reliability analysis in PLS-SEM.

Table 3. Construct Reliability and Validity

Construct	Cronbach's Alpha	Composite Reliability	AVE
Learning Style Identification (X1)	0.852	0.900	0.693
Learning Environment Optimization (X2)	0.884	0.915	0.684
Academic Performance (Y)	0.888	0.915	0.641
Student Educational Costs (Z)	0.867	0.904	0.653

Source: Processed Data (2025)

As illustrated in Table 3, all constructs surpass the recommended thresholds for Cronbach's Alpha (> 0.70), Composite Reliability (> 0.70), and AVE (> 0.50). This confirms that the constructs are valid and reliable, demonstrating the adequacy of the measurement model for further structural testing.

Table 4. Discriminant Validity Test Using Fornell–Larcker Criterion

Construct	X1	X2	Y	Z
X1	0.832			
X2	0.548	0.827		
Y	0.647	0.644	0.801	
Z	0.590	0.612	0.668	0.808

Source: Processed Data (2025)

As shown in Table 4, the square roots of the AVE values for all constructs are greater than their respective inter-construct correlations, confirming that each variable achieves discriminant validity. These results indicate that the constructs are distinct and suitable for further structural model analysis.

Table 5. Hypothesis Testing (Bootstrapping, N = 5,000)

Hypothesis	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Remarks

X1 → Y	0.421	0.425	0.079	5.308	0.000	Significant
X1 → Z	0.255	0.255	0.094	2.694	0.007	Significant
X2 → Y	0.413	0.416	0.081	5.100	0.000	Significant
X2 → Z	0.234	0.230	0.103	2.269	0.024	Significant
Y → Z	0.380	0.385	0.121	3.139	0.002	Significant

Note: Significant at ($p < 0.05$)
Source: Primary Data Processed (2025)

As displayed in Table 5, all proposed hypotheses were accepted since the t-statistics exceeded the critical value of 1.96 and the p-values were below 0.05. Learning Style Identification (X1) was found to significantly affect Academic Performance (Y) ($\beta = 0.421$, $t = 5.308$, $p < 0.001$) and Student Educational Costs (Z) ($\beta = 0.255$, $t = 2.694$, $p = 0.007$). Learning Environment Optimization (X2) also demonstrated significant effects on Academic Performance (Y) ($\beta = 0.413$, $t = 5.100$, $p < 0.001$) and Student Educational Costs (Z) ($\beta = 0.234$, $t = 2.269$, $p = 0.024$). Additionally, Academic Performance (Y) significantly influenced Student Educational Costs (Z) ($\beta = 0.380$, $t = 3.139$, $p = 0.002$). Overall, these results confirm statistically significant relationships among all constructs, validating the model at the 5% significance level.

Table 6. Indirect Effect

Hypothesis	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Remarks
X1 → Y → Z	0.160	0.164	0.062	2.591	0.010	Significant
X2 → Y → Z	0.157	0.159	0.057	2.736	0.006	Significant

Note: Significant at ($p < 0.05$)
Source: Primary Data Processed (2025)

As shown in Table 6, Academic Performance significantly mediates the effects of both X1 and X2 on Z. The indirect effect of X1 → Y → Z is significant ($\beta = 0.160$, $t = 2.591$, $p = 0.010$), and the indirect effect of X2 → Y → Z is also significant ($\beta = 0.157$, $t = 2.736$, $p = 0.006$). These results confirm that Academic Performance plays an essential mediating role in linking learning style identification and learning environment optimization to student educational cost reduction.

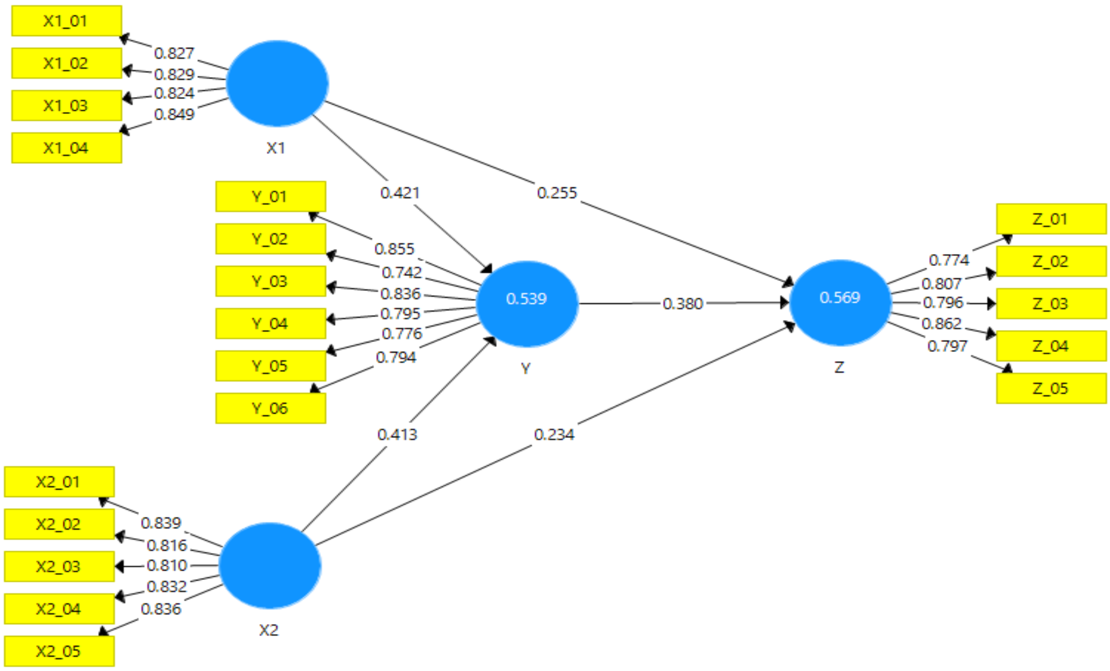
Table 7. R Square and R Square Adjusted

Construct	R Square	R Square Adjusted
Academic Performance (Y)	0.539	0.531
Student Educational Costs (Z)	0.569	0.558

Source: Primary Data Processed (2025)

Table 7 shows that Academic Performance ($R^2 = 0.539$; Adj. $R^2 = 0.531$) and Student Educational Costs ($R^2 = 0.569$; Adj. $R^2 = 0.558$) are moderately explained by the predictors, exceeding the 0.50 threshold suggested by Hair et al. (2019). The slightly higher R^2 for Student Educational Costs indicates stronger explanatory power compared to Academic Performance. The small gap between R^2 and Adjusted R^2 values confirms model stability and suggests no overfitting, supporting the model's predictive relevance.

Figure 2. Structural Model with Path Coefficient



The structural model shows significant relationships among all constructs. VARK learning style identification (X1) positively affects academic performance (β = 0.421) and student educational cost reduction (β = 0.255). Learning environment optimization (X2) also enhances academic performance (β = 0.413) and reduces educational costs (β = 0.234). In addition, academic performance (Y) strongly influences student educational cost reduction (β = 0.380). These results confirm that both X1 and X2 improve student outcomes directly and indirectly through academic performance.

Summary of Results

The model demonstrates moderate explanatory power, with Academic Performance (R^2 = 0.539) and Student Educational Costs (R^2 = 0.569) explained by the predictor variables. All hypotheses are supported, with path coefficients ranging from 0.234 to 0.421. VARK learning style identification (β = 0.421) and learning environment optimization (β = 0.413) exert the strongest effects on Academic Performance, while Academic Performance mediates their influence on educational cost reduction. These findings confirm the model's effectiveness in improving learning outcomes and reducing student educational expenses.

DISCUSSION

The Influence of Learning Style Identification on Academic Performance

Learning style identification (X1) significantly improves academic performance (β = 0.421, $p < 0.001$), consistent with prior studies affirming the relevance of the VARK framework in higher education (Coffield et al., 2024; Mohsenipouya et al., 2024). When students recognize their preferred learning styles, they are better able to select strategies that enhance understanding, engagement, and information retention, thereby improving academic outcomes.

The Influence of Learning Style Identification on Student Educational Costs

The results indicate that learning style identification (X1) significantly reduces student educational costs (β = 0.255, $p < 0.01$), supporting H2. Students who adopt effective learning strategies complete academic tasks more efficiently, reducing the likelihood of repeating courses or extending study duration. This finding is aligned with Tran (2021), who reported that structured academic strategies increase learning efficiency and decrease overall educational expenses.

The Influence of Learning Environment Optimization on Academic Performance

Findings confirm that learning environment optimization (X2) positively influences academic performance ($\beta = 0.413$, $p < 0.001$). Supportive environments that include digital platforms, adequate learning facilities, and flexible academic arrangements increase student engagement and success. This aligns with evidence emphasizing the value of student-centered and technology-enhanced environments (Lacka et al., 2021; Alenezi, 2023). Additionally, Lusa et al. (2022) and Kobicheva et al. (2022) highlight the role of blended learning and innovative instructional spaces in improving educational effectiveness.

The Influence of Learning Environment Optimization on Student Educational Costs

Optimized learning environments (X2) significantly reduce student educational costs ($\beta = 0.234$, $p < 0.05$). Institutions that adopt technology-based instructional approaches minimize indirect expenses by improving efficiency and reducing the need for additional semesters or supplementary learning materials. Similar findings by Alenezi (2023) and Kobicheva et al. (2022) indicate that flexible learning systems reduce financial burden, while Ranjith et al. (2021) demonstrated how digital transformation improves efficiency, a principle transferable to higher education cost management.

The Mediating Role of Academic Performance

Academic performance (Y) significantly reduces student educational costs ($\beta = 0.380$, $p < 0.01$) and mediates the effects of both learning style identification ($X1 \rightarrow Z$, $\beta = 0.160$, $p < 0.01$) and learning environment optimization ($X2 \rightarrow Z$, $\beta = 0.157$, $p < 0.01$). Improved academic outcomes lead to timely program completion and reduced unnecessary expenses. These results are consistent with Wu et al. (2019) and Tran (2021), who demonstrated that academic success is closely associated with efficiency in higher education.

Managerial and Practical Implications

This study provides several practical implications for universities and policymakers. Early assessment of learning styles can enhance academic effectiveness and efficiency. Investment in digital and blended learning environments can further strengthen student engagement and reduce educational costs. Linking academic achievement with financial incentives, such as scholarships or tuition discounts, may reinforce the value of academic performance in minimizing financial burden.

Limitations and Directions for Future Research

This study is limited by its relatively small sample size ($N = 125$) and reliance on self-reported questionnaire responses, which may limit generalizability and introduce potential response bias. Future research should involve larger and more diverse populations and explore additional intervening variables such as digital readiness, learning motivation, and socio-economic background.

CONCLUSION

This study demonstrates that identifying VARK learning styles and optimizing the learning environment significantly enhance academic performance and reduce student educational costs. Academic performance also mediates these relationships, indicating that effective educational outcomes depend not only on financial investment but also on instructional strategies aligned with students' learning preferences. These findings underscore the importance of personalized learning and supportive educational environments in reducing financial burden and promoting sustainable educational systems. Future research should incorporate broader samples and additional moderating variables to enrich understanding of how learning strategies optimize human capital development.

ACKNOWLEDGMENT
The authors express sincere appreciation to the students of Universitas Cenderawasih for their participation and valuable contributions, and to the university for the institutional support and academic environment that made this study possible.

DECLARATION OF CONFLICTING INTERESTS
The authors have declared no potential conflicts of interest concerning the study, authorship, and/or publication of this article.

REFERENCES

Alenezi, M. (2023). Digital learning and digital institution in higher education. *Education Sciences*, *13*(1), 88. https://doi.org/10.3390/educsci13010088

Amir, H., Bilal, K., & Khan, M. I. (2023). Efficacy of investment in educational institutes and human capital for sustainable economic growth in pakistan. *Annals of Human and Social Sciences*, *4*(2), 586-598. https://doi.org/10.35484/ahss.2023(4-II)54

Coffield, F., Moseley, D., Hall, E., & Ecclestone, K. (2004). *Learning styles and pedagogy in post-16 learning: A systematic and critical review*. Learning & Skills Research Centre.

College Board. (2024). *Trends in college pricing and student aid 2024*. College Board.

El-Saftawy, E., Latif, A. A. A., ShamsEldeen, A. M., Alghamdi, M. A., Mahfoz, A. M., & Aboulhoda, B. E. (2024). Influence of applying VARK learning styles on enhancing teaching skills: application of learning theories. *BMC medical education*, *24*(1), 1034. https://doi.org/10.1186/s12909-024-05979-x

Falch, T., Iversen, J. M. V., Nyhus, O. H., & Strøm, B. (2022). Quality measures in higher education: Norwegian evidence. *Economics of Education Review*, *87*, 102235. https://doi.org/10.1016/j.econedurev.2022.102235

Fleming, N., & Baume, D. (2006). Learning Styles Again: VARKing up the right tree!. Educational developments, 7(4), 4.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2019). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). SAGE Publications.

Han, F. (2023). Relations between students' study approaches, perceptions of the learning environment, and academic achievement in flipped classroom learning: Evidence from self-reported and process data. *Journal of Educational Computing Research*, *61*(6), 1252-1274. https://doi.org/10.1177/07356331231162823

Isaeva, R., Karasartova, N., Dznunusnalieva, K., Mirzoeva, K., & Mokliuk, M. (2025). Enhancing learning effectiveness through adaptive learning platforms and emerging computer technologies in education. *Jurnal Ilmiah Ilmu Terapan Universitas Jambi*, *9*(1), 144-160. https://doi.org/10.22437/jiituj.v9i1.37967

Kee, D. M. H., Xuan, S. T. H., Yi, S. H., Itnes, S. Bin, Saseetharan, S. S. V. A., Shu, S., & Dehao, D. (2025). Money matters: The power of financial literacy on university student spending decisions. *Asian Pacific Journal of Management and Education*, *8*(1), 134–149. https://doi.org/10.32535/apjme.v8i1.3857

Kobicheva, A., Tokareva, E., & Baranova, T. (2022). Students' affective learning outcomes and academic performance in the blended environment at university: comparative study. *Sustainability*, *14*(18), 11341. https://doi.org/10.3390/su141811341

Lacka, E., Wong, T. C., & Haddoud, M. Y. (2021). Can digital technologies improve students' efficiency? Exploring the role of Virtual Learning Environment and Social Media use in Higher Education. *Computers & Education*, *163*, 104099. https://doi.org/10.1016/j.compedu.2020.104099

Lee, C. S., Chen, Y. C., Chiang, M. C., & Lin, C. J. (2024). Unforgettable food experiences: A model for constructing rural tourism cooking experience classrooms. *Quality & Quantity*, *58*(6), 5445-5462. https://doi.org/10.1007/s11135-024-01903-z

Lee, S. (2025). Educational implications of VARK learning styles: Academic performance and pedagogical preferences among Korean pharmacy students. *Indian Journal of Pharmaceutical Education and Research*, *59*(2), 512–517. https://doi.org/10.5530/ijper.20250050

Lusa, H., Adnan, A., & Yurniawati, Y. (2022). Effect of blended learning on students' learning outcomes: A meta-analysis. *Jurnal Pendidikan Progresif*, *12*(2), 309-325. https://doi.org/10.23960/jpp.v11.i2.202113

Marlina, E., Tjahjadi, B., & Ningsih, S. (2021). Factors affecting student performance in e-learning: A case study of higher educational institutions in Indonesia. *The Journal of Asian Finance, Economics and Business*, *8*(4), 993-1001.

Mohsenipouya, H., Monsefi, S. F., Hosseinnataj, A., Mamun, M. A., & Al-Mamun, F. (2024). The effect of learning styles on the academic achievement of nursing students: a cross-sectional study. *BMC Research Notes*, *17*(1), 294. https://doi.org/10.1186/s13104-024-06949-8

Mozaffari, H. R., Janatolmakan, M., Sharifi, R., Ghandinejad, F., Andayeshgar, B., & Khatony, A. (2020). The relationship between the VARK learning styles and academic achievement in dental students. *Advances in medical education and practice*, 15-19. https://doi.org/10.2147/AMEP.S235002

Mulyawan, B., & Christanti, T. S. V. (2022, April). An application performance measurement model for higher education in Indonesia. *In 3rd Tarumanagara International Conference on the Applications of Social Sciences and Humanities (TICASH 2021)* (pp. 2053–2057). Atlantis Press. https://doi.org/10.2991/assehr.k.220404.337

Noor, S. N. A. M., & Ramly, M. K. A. (2023). Bridging learning styles and student preferences in construction technology education: VARK model analysis. *International Journal of Academic Research in Progressive Education and Development*, *12*(3), 2075-2085. http://dx.doi.org/10.6007/IJARPED/v12-i3/19313

Ranjith, P. V., Madan, S., Ang Wern Jian, D., Teoh, K. B., Singh, A. S., Ganatra, V., Akshay, A. V., Rana, R., Das, A., Shekar, L., & Singh, P. (2021). Harnessing the power of artificial intelligence in the accounting industry: A case study of KPMG. *International Journal of Accounting & Finance in Asia Pacific, 4*(2), 93–106. https://doi.org/10.32535/ijafap.v4i2.1117

Rusticus, S. A., Pashootan, T., & Mah, A. (2023). What are the key elements of a positive learning environment? Perspectives from students and faculty. *Learning environments research*, *26*(1), 161-175. https://doi.org/10.1007/s10984-022-09410-4

Tran, C. D. T. T. (2021). Cost efficiency–one size fits all? A university-level analysis of economies of scale and scope in Vietnamese higher education. *Asia Pacific Journal of Education*, *41*(2), 336-355. https://doi.org/10.1080/02188791.2020.1735996

World Bank. (2023). *World development report 2023: Investing in human capital for sustainable growth*. World Bank. https://www.worldbank.org/en/news/feature/2023/05/25/investing-in-human-capital-for-a-greener-future

Wu, J., Wei, X., Zhang, H., & Zhou, X. (2019). Elite schools, magnet classes, and academic performances: Regression-discontinuity evidence from China. *China Economic Review*, *55*, 143-167. https://doi.org/10.1016/j.chieco.2019.03.004

ABOUT THE AUTHOR(S)

1st Author
Lisa Gresti Sella Damanik is a lecturer and researcher in the Management Study Program, Faculty of Economics and Business, Universitas Cenderawasih, Papua, Indonesia. She holds a Bachelor's and Master's degree in Management and currently serves as a faculty member specializing in Human Resource Management and educational development. Her research interests include learning effectiveness, educational cost efficiency, and strategic human capital investment. She actively participates in academic conferences and community-based research initiatives in Papua. Email: lisa.damanik@feb.uncen.ac.id.

2nd Author
Xenia Irene Sandy Landjang is a lecturer and academic researcher in the Management Study Program, Faculty of Economics and Business, Universitas Cenderawasih, Papua, Indonesia. She earned her Master's degree in Management and is dedicated to research in organizational behavior, digital learning strategies, and performance optimization in higher education. She has contributed to several national and international academic forums.