International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(7s) 2026 pp. 1216-1225
https://doi.org/10.70917/ijcisim-2026-3192
Article

Towards Learner-Centered Educational Technologies: Analyzing the Alignment of Teaching and Learning Styles in Philippine High Schools

Myla Polines Millondaga

Department of General Teacher Training, North Eastern Mindanao State University, Tandag City, Surigao del Sur 8300, Philippines
Correspondence: mpmillondaga@nemsu.edu.ph

Abstract: As educational technologies become increasingly integral to Philippine high schools, aligning digital interfaces with users' cognitive preferences remains a critical challenge. This study models the instructional alignment between students' learning styles and teachers' teaching styles to provide empirical data architecture for designing Adaptive Learning Systems (ALS). Utilizing a quantitative correlational-predictive design, data from 319 students and 77 teachers in Surigao del Sur were computationally analyzed using the Grasha-Riechmann frameworks. Findings revealed that students predominantly preferred a collaborative learning style, while teachers primarily adopted a facilitative instructional approach. Predictive modeling indicated that students' learning preferences did not significantly differ by sex or school type, offering a streamlined, demographic-agnostic baseline for machine learning algorithms. Conversely, teachers' educational background significantly predicted their instructional deployment. By quantitatively clustering these behavioral profiles into distinct instructional models, this research translates pedagogical constructs into computational parameters. The resulting data blueprints enable software engineers to develop AI-integrated platforms and collaborative digital workspaces that dynamically adapt to users' specific configurations, thereby optimizing human-computer interaction and system efficiency in modern digital education.

Keywords: adaptive learning systems, educational data analytics, human-computer interaction, learning styles, predictive modeling

1. Introduction

Despite the rapid proliferation of computer information systems in education, there remains a critical gap in modeling the alignment between students' learning preferences and teachers' instructional styles to design effective, learner-centered adaptive technologies in the Philippine high school context. Philippine high schools are increasingly heterogeneous, necessitating instructional approaches that are flexible and responsive to enhance student engagement and academic achievement (Abdurahim-Salain et al., 2026; Bantillo et al., 2024; Chavez et al., 2026). Relying on a single teaching approach or a static digital interface is no longer sufficient to address the varying ways students acquire and process knowledge. Therefore, integrating learning styles into adaptive e-learning systems is crucial, as this knowledge allows systems to offer valuable advice and instructions to students and teachers to optimise students' learning process (Truong, 2016).

Learning style refers to an individual's relatively stable pattern of perceiving, processing, and responding to information during the learning process (Delina et al., 2025). Aligning pedagogical and technological instruction with these preferences facilitates the transfer of information into long-term memory (Wiangga, 2024). The implementation of differentiated, learner-centered instruction, whether delivered by a human educator or personalized through Artificial Intelligence (AI), significantly improves students' academic performance and classroom engagement (Bibi

& Bagum, 2025; Shala et al., 2024; Du Plooy et al., 2024). To achieve this within digital platforms, learner modeling methods are essential for system adaptation (Popescu et al., 2010). Researchers propose estimating these learning styles by using structured questionnaires alongside rule-based methods that track learner activity within a Learning Management System (LMS) (Liyanage et al., 2014).

A mismatch between teaching styles and learning preferences is consistently associated with lower levels of student satisfaction and academic achievement (Asrifan et al., 2025). This discrepancy extends heavily into Human-Computer Interaction (HCI) within educational technology. Strong evidence indicates that students who learned with learning style-fit versions showed significantly better learning achievement than those who learned with non-fit versions (Hwang et al., 2013). Critically, because student choices are often not related to their cognitive process or learning style, learners cannot reliably self-select appropriate interfaces, underscoring the absolute necessity for systems to adapt automatically (Hwang et al., 2013). Even from early childhood, cognitive styles dictate how children interact with educational resources and teacher guidance (Fajarwati et al., 2026; Wanmei, 2025), emphasizing that learning environments must be technologically and pedagogically responsive from the ground up.

Empirical evidence on this human-to-system instructional alignment remains limited within the Philippine educational context. Meaningful learning requires instructional strategies adapted to varying strengths, experiences, and preferences (Ampong, 2026; Montecalvo, 2026; Putri, 2025; Ramadani & Inayati, 2024). Local studies show that Filipino secondary students often exhibit multimodal learning preferences, yet face a mismatch because teachers predominantly rely on visual instructional approaches (Balonda & Dollente, 2025). Certain modalities, such as visual, auditory, and collaborative styles, have proven vital for students developing strong digital competence (Erie, 2025). Similarly, students in the Mountain Province prefer visual, auditory, and tactile modalities (Casido, 2026), while students in Misamis Oriental demonstrate primary auditory preferences requiring tailored interventions (Paypa et al., 2024). Teachers recognize the importance of strong instructional alignment but are frequently restricted by classroom constraints, limited time, and a lack of resources (Casido, 2026), limitations that the strategic deployment of adaptive educational technologies can alleviate.

To construct accurate data models for educational information systems, teaching and learning styles must be analyzed as interrelated constructs. The Grasha–Riechmann model provides a highly relevant framework for this computational mapping by identifying five instructional approaches (Expert, Formal Authority, Personal Model, Facilitator, and Delegator) alongside six corresponding learning styles (Independent, Dependent, Collaborative, Participant, Avoidant, and Competitive) (Ramirez et al., 2025; Sim et al., 2022). Expanding research on these diverse classroom settings is essential. By exploring the teaching and learning styles of Filipino high school students and teachers, this study advances current knowledge on instructional alignment and provides the empirical foundation necessary for designing learner-centered educational technologies and data-driven interventions.

2. Methods

Research Design

This study employed a quantitative, cross-sectional, non-experimental correlational-predictive research design to model the factors influencing teaching and learning styles. In the context of educational information systems, this analytical approach is crucial for establishing the foundational data architecture required to engineer adaptive learning technologies. By describing teaching and learning styles, examining their computational relationships, and determining whether selected demographic variables significantly predicted variations in these educational constructs without manipulating the study variables (Gómez-Tabares et al., 2022; Wahyuni et al., 2025), this study provides empirical data that can help align both human instruction and digital system interfaces with students' learning preferences.

Participants of the Study

The dataset was derived from participants located in Carrascal, Cantilan, Madrid, Carmen, and Lanuza (CarCanMadCarLan) in Surigao del Sur, Philippines. A total of 319 students and 77 teachers were randomly selected through online sampling to participate in this study. The utilization of online sampling facilitated efficient digital data collection, enabling researchers to capture data across geographically dispersed schools while minimizing time, travel, and administrative costs (Mariya et al., 2023). Furthermore, it provided respondents with the flexibility to interact with the survey at their convenience using internet-enabled devices, yielding a robust dataset suitable for demographic and instructional profiling.

Instrumentation

Data acquisition was conducted using two structured and validated digital questionnaires designed for user profiling. The Teaching Style Questionnaire, administered to teachers, consisted of 40 items adapted from the Grasha Teaching Style Inventory (GTSI). It measured five dimensions of teaching style (Expert, Formal Authority, Personal Model, Facilitator, and Delegator) to establish the instructional parameters of the educators. The Learning Style Questionnaire, administered to students, comprised 60 items adapted from the Grasha–Riechmann Student Learning Style Scales (GRSLSS). This instrument assessed six learning style dimensions for student profiling: Independent, Dependent, Collaborative, Participative, Avoidant, and Competitive.

Both questionnaires utilized a 5-point Likert scale, with responses ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), allowing respondents to quantify the extent of their teaching or learning preferences. Prior to actual data collection, the instruments underwent content validation by subject-matter experts to establish relevance and clarity. A pilot test was subsequently conducted among respondents with characteristics matching the target population to determine instrument reliability, identify ambiguous items, and ensure the validity of the data inputs before full-scale deployment.

Data Collection

Data collection was executed in coordination with the school administrators of the participating institutions. Strict ethical standards for data privacy and human-subject research were observed. This included obtaining necessary institutional approvals, securing informed consent from all participants (and parental consent where applicable), ensuring voluntary participation, guaranteeing the anonymity and confidentiality of the digital responses, and informing participants of their right to withdraw from the study at any stage.

Data Analysis

Following data acquisition, all completed digital questionnaires were pre-processed to check for completeness, coded, and encoded into statistical software for quantitative analysis. Responses to the 5-point Likert scales were scored and aggregated according to the respective dimensions of the GTSI and the GRSLSS. For each respondent, the teaching or learning style with the highest composite score was identified as the dominant style, serving as the categorical outcome variable in the subsequent predictive modeling.

Descriptive statistics, specifically frequency counts and percentages, were employed to summarize the demographic characteristics of the respondents and to map the distribution of teaching and learning styles. To determine whether demographic profiles significantly influenced teaching and learning styles, multinomial logistic regression was performed using Likelihood Ratio Tests. Multinomial logistic regression served as the predictive data modeling technique for identifying significant predictors, as both the teaching and learning style frameworks consist of multiple nominal categories. Statistical tests were evaluated at the 0.05 level of significance. The resulting analysis clustered the learning and teaching styles, providing the mathematical and behavioral foundations necessary for integrating learner-system alignment in future educational technologies.

3. Results

RQ1: What are the preferred learning styles of the students?

Table 1 presents the data distribution of preferred learning profiles based on the students' sex (male, female). Out of the 319 student respondents, 137 (42.95%) were male and 182 (57.05%) were female.

The Collaborative learning style emerged as the most prevalent profile, accounting for 36.50% of male respondents and 42.31% of female respondents, representing a total of 127 students (39.81%). This finding indicates that most students favor learning environments characterized by peer interaction and the exchange of ideas, suggesting that educational technologies and digital platforms should prioritize collaborative interfaces (e.g., peer-to-peer forums, shared digital workspaces) to maximize engagement.

The Dependent learning style ranked second in prevalence, comprising 24.82% of male respondents and 23.08% of female respondents, or 76 students (23.82%) overall. This was followed by the Independent learning style, which accounted for 16.61% of the total sample. Generally, the baseline distribution of preferred learning profiles was symmetric between male and female students.

Table 1. Preferred learning styles based on students' sex

Learning Styles	Male	Female	Total
	n	**%**	**n**
Independent	24	17.52%	29
Avoidant	9	6.57%	10
Collaborative	50	36.50%	77
Dependent	34	24.82%	42
Competitive	5	3.65%	9
Participant	15	10.95%	15
Total	**137**	**100.00%**	**182**

Table 2 delineates the distribution across school architectures, indicating that the Collaborative learning style was the most prevalent among public school students (39.62%), followed by the Dependent (23.90%) and Independent (16.67%) learning styles. In contrast, the Participant, Avoidant, and Competitive learning styles were the least preferred. These findings confirm that the primary end-users (students) generally favor interactive and cooperative system environments over highly competitive or isolated digital learning approaches.

Table 2. Preferred learning styles based on students' school type

Learning Styles	Public	Private	Total
	n	**%**	**n**
Independent	53	16.67%	0
Avoidant	19	5.97%	0
Collaborative	126	39.62%	1
Dependent	76	23.90%	0
Competitive	14	4.40%	0
Participant	30	9.43%	0
Total	**318**	**100.00%**	**1**

RQ2: What is the distribution of teaching styles of teachers?

Table 3 models the distribution of teaching styles according to the sex of the teachers, acting as a baseline for instructor profiling. The Facilitator teaching style was the most prevalent among both male (47.06%) and female (36.67%) teachers, suggesting that teachers favor learner-centered instructional approaches that promote active knowledge construction.

The Expert teaching style ranked second and was more frequently observed among female teachers (35.00%) than male teachers (17.65%), indicating a greater tendency among female respondents to emphasize subject matter expertise and knowledge transmission. In contrast, male teachers exhibited a higher proportion of the Facilitator style. Meanwhile, the Formal Authority and Personal Model teaching styles were the least represented among both demographic groups.

Table 3. Teaching styles based on teachers' sex

Teaching Styles	Male	Female	Total
	n	**%**	**n**

Expert	3	17.65%	21
Formal Authority	1	5.88%	6
Personal Model	5	29.41%	11
Facilitator	8	47.06%	22
Total	**17**	**100.00%**	**60**

Table 4 presents the distribution of teaching styles correlated with teachers' highest educational attainment. Teachers holding a bachelor's degree predominantly exhibited the Facilitator teaching style (40.63%), whereas master's degree holders most frequently demonstrated the Expert teaching style (50.00%), reflecting a structured shift toward knowledge transmission in highly educated cohorts.

Table 4. Teaching styles based on teachers' educational attainment

Teaching Styles	**Bachelor**	**Masters**	**Doctor**	**Total**
	n	**%**	**n**	**%**
Expert	18	28.13%	6	50.00%
Formal Authority	6	9.38%	0	0.00%
Personal Model	14	21.88%	2	16.67%
Facilitator	26	40.63%	4	33.33%
Total	**64**	**100.00%**	**12**	**100.00%**

Table 5 tracks instructional variations against teachers' length of service. Novice educators (less than one year of experience) exclusively exhibited the Expert teaching style (100%). Among mid-career professionals (1–10 years and 11–20 years), the Facilitator style became predominant (47.62% and 36.36%, respectively). Conversely, veteran teachers (31 years or more) reverted to the Expert style (57.14%), indicating dynamic shifts in instructional deployment over a professional lifecycle.

Table 5. Teaching styles based on teachers' length of service

Teaching Styles	**<1 year**	**1 – 10 years**	**11 – 20 years**	**21 – 30 years**	**>31 years**	**Total**
	n	**%**	**n**	**%**	**n**	**%**
Expert	2	100%	11	26.19%	5	22.73%
Formal Authority	0	0%	3	7.14%	2	9.09%
Personal Model	0	0%	8	19.05%	7	31.82%
Facilitator	0	0%	20	47.62%	8	36.36%
Total	**2**	**100%**	**42**	**100%**	**22**	**100%**

RQ3: Does students' demographic profile influence their learning style?

Table 6 presents the predictive modeling results utilizing likelihood ratio tests to examine the effects of sex and school type on students' learning styles. The statistical outcomes indicate that sex did not have a statistically significant effect on learning profiles ($\chi^2 = 1.824$, $p = 0.873$). Similarly, school type was not a significant predictor ($\chi^2 = 1.728$, $p = 0.885$). From a systems design perspective, these findings suggest that a unified algorithmic approach to learning style identification can be deployed across these demographic variables without requiring sex- or school-specific branching logic.

Table 6. Influence of students' demographic profile to their preferred learning style

Effect	-2 Log Likelihood	χ2	Sig.
Intercept	44.169	0.000	-
Sex	45.993	1.824	0.873
School Type	45.897	1.728	0.885

RQ4: Does teachers' demographic profile influence their teaching style?

Table 7 details the predictive analysis regarding teachers' demographic characteristics. Sex did not significantly influence teaching style ($\chi^2 = 5.022$, $p = 0.170$), and years in teaching was not a statistically significant predictor ($\chi^2 = 17.467$, $p = 0.133$). In contrast, educational background significantly influenced teaching style ($\chi^2 = 13.355$, $p = 0.038$). This implies that adaptive systems aiming to assist educators might require personalized configurations and interface adaptations strictly based on the user's academic preparation level rather than their age, tenure, or sex.

Table 7. Influence of teachers' demographic profile to their teaching style

Effect	-2 Log Likelihood	χ2	Sig.
Intercept	48.899	0.000	-
Sex	53.921	5.022	0.170
Educational Background	62.254	13.355	0.038
Years in Teaching	66.366	17.467	0.133

RQ5: How are learning styles and teaching styles clustered?

Table 8 presents the data clustering of dominant instructional and learner profiles, serving as the architectural blueprint for mapping human-to-system instructional alignment.

Cluster 1 models a rigid, teacher-directed profile (40.26% instructional dominance), aligning Expert/Formal Authority approaches with Dependent/Participant/Competitive learners (37.61%). This maps to environments requiring highly structured, centralized content delivery. Cluster 2 mirrors this but integrates the Personal Model, catering to demonstrative learning experiences.

Conversely, Clusters 3 and 4 represent decentralized, learner-centered profiles. Cluster 3 exhibits the highest instructional prevalence (90.91% cumulative), successfully mapping Facilitator models with Collaborative/Independent learners (65.82%). This cluster provides the strongest empirical evidence for designing adaptive learning networks that promote distributed knowledge construction and self-directed user interactions.

Table 8. Different clusters of learning styles and teaching styles

Cluster	Dominant Teaching Style(s)	Teaching Style (%)	Dominant Learning Style(s)	Learning Style (%)	Description of the Cluster
1	Expert, Formal Authority	**40.26**	Dependent, Participant, Competitive	**37.61**	**Teacher-directed instructional cluster.** This cluster represents classrooms where teachers primarily emphasize subject expertise and instructional

					authority, while students exhibit structured, teacher-guided, and achievement-oriented learning preferences.
2	Personal Model, Expert, Formal Authority	**61.04**	Participant, Dependent, Competitive	**37.61**	**Demonstrative and structured learning cluster.** Teachers combine subject expertise with modeling of skills and authoritative instruction, whereas students demonstrate preferences for guided participation, structured learning, and moderate academic competition.
3	Facilitator, Personal Model, Expert	**90.91**	Collaborative, Participant, Independent	**65.82**	**Learner-centered collaborative cluster.** Teachers predominantly employ facilitative and modeling approaches while maintaining content expertise, creating learning environments that encourage collaboration, active participation, and independent learning among students.
4	Facilitator, Expert	**70.13**	Independent, Collaborative, Participant	**65.82**	**Balanced facilitative–expert cluster.** Teachers integrate learner-centered facilitation with strong content knowledge, supporting students who prefer independent learning while also valuing collaboration and

					active classroom participation.

4. Discussion

The primary contribution of this study lies in translating pedagogical constructs into computational parameters for Information and Communications Technology (ICT). While previous research has largely treated teaching and learning styles as abstract educational concepts, this study provides the empirical data architecture required to engineer learner-centered adaptive technologies and AI-integrated educational systems.

Primary findings revealed that students' learning styles did not differ based on their sex and type of school. Similarly, teachers' teaching styles did not differ based on their sex and years in teaching but did differ based on their educational background. From a systems engineering perspective, this is a highly novel contribution. It establishes that predictive algorithms within an Adaptive Learning System (ALS) do not require complex, branching demographic logic to accommodate sex or school type. Instead, software developers can utilize streamlined, rule-based methods to estimate learning styles based on user activity (Liyanage et al., 2014), creating demographic-agnostic baseline algorithms that reduce computational overhead while maximizing system efficiency. Furthermore, knowing that educational background influences teaching styles allows for the creation of tailored digital dashboards that automatically adapt to an educator's academic profile.

The predominance of the collaborative learning style among students suggests that learners benefit most from instructional environments that promote interaction, cooperation, and shared knowledge construction. For Human-Computer Interaction (HCI) and educational platform design, this mandates a shift away from isolated, static digital modules. Modern intelligent Learning Management Systems (LMS) must prioritize collaborative interfaces, such as AI-moderated peer-to-peer forums, synchronized digital workspaces, and interactive project-based environments. Evidence strictly dictates that students cannot reliably self-select the digital interfaces that best fit their cognitive processes (Hwang et al., 2013). Therefore, embedding these identified learning preferences into the system's core logic allows the technology itself to automatically offer valuable advice and optimized instructions to the student (Truong, 2016), bypassing the risk of user-selection error.

The predominance of the facilitator teaching style among teachers reflects an instructional orientation that aligns well with students' collaborative learning preferences. When designing intelligent tutoring systems, the AI agent must mirror this facilitative approach, acting as a guide that encourages inquiry and digital discussion rather than merely operating as a rigid, authoritative data repository. However, the presence of teachers who predominantly employ the expert, formal authority, and personal model teaching styles highlights the need for instructional flexibility. To be truly effective, an adaptive educational system must accommodate these varying instructional styles through continuous learner modeling (Popescu et al., 2010), dynamically shifting the AI's teaching persona based on real-time data inputs and the specific lesson objectives.

The most significant technological contribution of this research is the quantitative clustering of teaching and learning styles. The identification of distinct behavioral profiles, such as the teacher-directed instructional profile in Cluster 1 or the learner-centered collaborative profile in Cluster 3, provides a direct, data-driven blueprint for training machine learning algorithms. Instead of relying on randomized digital interventions, AI models can utilize these established clusters to automatically align the system's instructional delivery with the user's precise learning profile. Deploying this learning style-fit version of instruction directly eliminates the digital mismatches that historically lead to lower academic achievement and poor user engagement (Asrifan et al., 2025; Hwang et al., 2013). By bridging the Grasha-Riechmann framework with computational clustering, this study establishes a robust foundational framework for the next generation of intelligent, responsive educational technologies.

5. Conclusion

The translation of pedagogical profiles into computational data architectures is a necessary foundational step for engineering intelligent, learner-centered educational technologies. By utilizing established instructional clusters as training blueprints for machine learning algorithms, educational platforms can bypass the limitations of static digital interfaces and user-selection errors. The demographic-agnostic nature of student learning preferences significantly reduces computational overhead, allowing software developers to deploy streamlined, universally applicable adaptive logic across diverse digital learning environments.

To operationalize these architectural models, developers of Learning Management Systems (LMS) must integrate automated, rule-based profiling algorithms that continuously assess user activity to dynamically adapt the system's instructional delivery mechanics. Furthermore, user interfaces should prioritize collaborative and interactive digital workspaces, such as AI-moderated peer-to-peer forums, to directly accommodate the predominant collaborative learning preferences of system end-users. Educational IT administrators should also utilize the mapped instructional clusters to procure and deploy adaptive software capable of manifesting flexible teaching personas, ranging from facilitative to expert models, ensuring digital infrastructure aligns seamlessly with classroom behavioral dynamics.

Advancing this domain requires future research to focus on programming and deploying a prototype Adaptive Learning System (ALS) that explicitly utilizes the identified teaching-learning clusters to structure its underlying Artificial Intelligence architecture. Empirical studies must conduct real-time algorithmic validation through A/B testing of learning style-fit versus non-fit digital interfaces within Philippine high schools to precisely quantify the impact of algorithmic alignment on digital engagement and knowledge retention. Finally, subsequent investigations should employ Educational Data Mining (EDM) over extended academic periods to track how users' digital learning profiles evolve in response to sustained interaction with AI-integrated educational platforms.

Acknowledgements

The author affirms that this study was independently carried out and reflects personal academic effort and critical analysis. All concepts, interpretations, and discussions presented in this paper were carefully developed by the author throughout the research process. Any use of artificial intelligence tools was strictly limited to minor language refinement, such as improving grammar and clarity of expression. These tools were not involved in developing the research ideas, conducting the analysis, interpreting the findings, or composing the substantive sections of the manuscript. The author fully assumes responsibility for the authenticity, accuracy, and originality of the entire work, including its analyses, interpretations, and conclusions.

References

1. Abdurahim-Salain, H., Salain, S. A., Indama, A. C., Paraman, M. H., & Chavez, J. V. (2026). Inclusive Education, Emotional Profiling and Empathy of Learners Towards Understanding Barriers and Promoting Strategic Teaching Adaptation. International Journal of Special Education, 41(3s), 177-195.
2. Almira, N. F., Almira, Z. F., Vircavani, C., & Agustina, E. (2025). A Systematic Review of Teachers' Teaching Styles and Their Impact on EFL Student Learning Outcomes. Journal of Applied Linguistics and English Education, 3(1), 1-15.
3. Ampong, T. A. (2026). Deliberate Teaching Strategies in Inclusive Science, Math, and ICT Classrooms: Motivating Diverse Learners to Innovate. International Journal of Special Education, 41(3s), 57-62.
4. Arslan, E., Özkaymak, A., & Dönmez, N. Ö. (2023). Clustering Students Based on Gamification User Types and Learning Styles. arXiv. https://doi.org/10.48550/arxiv.2310.14430
5. Asrifan, A., de Barros Cardoso, L. M. O., & Vargheese, K. J. (2025). Teacher-Student Style Mismatch: Implications for English Language Learning and Classroom Dynamics. Journal of English Language Studies, 10(2), 173-199.
6. Balonda, L. J. L., & Dollente, L. A. U. (2025). The impact of learning styles and teaching styles on second language learning success. Indonesian Journal of Education Research, 6(3), 321–330. https://doi.org/10.37251/ijoer.v6i3.1485
7. Bantillo, R. B., & Ngag, J. B. J. U. (2024). CHANGING LANDSCAPE OF FILIPINO EDUCATION: TEACHERS'PERSPECTIVES ON TRADITIONAL VS. MODERNIZED APPROACHES TO TEACHING FILIPINO. Ignatian International Journal for Multidisciplinary Research, 2(6), 2409-2420.
8. Bibi, A., & Bagum, M. (2025). Students' Learning Styles and their Academic Performance at Secondary Level. Journal of Social Sciences Research & Policy, 3(04), 371-385.
9. Casido, F. (2026). Learning Style Preferences of Grade 6 Learners and Teachers' Coping Strategies in Managing Diverse Learning Styles in Sagada District, Philippines. Journal of Education, Learning, and Management, 3(1), 372-386. https://doi.org/10.69739/jelm.v3i1.1898
10. Chavez, J. V. (2023). Assessing online academic integrity and humanized teaching in Zamboanga Peninsula Polytechnic State University. Journal of Multidisciplinary in Social Sciences, 19(1), 9-17.
11. Chavez, J. V., Salveleon, R. G., Eustaquio, M. T. L., Adalia, H. G., Rosaldo, M. P. T., Quinto, J. B., ... & Nazareth, I. M. (2026). Practices and strategies of informal assessments on grammar rules among second language learners. Int J Eval & Res Educ, 15(3), 2379-2389.
12. Delina, E. J., Apdoludin, A., & Aldino, A. (2025). Analysis of Learning Styles of Academically Achieving Students. Journal la sociale, 6(6), 1717-1724.
13. Du Plooy, E., Casteleijn, D., & Franzsen, D. (2024). Personalized adaptive learning in higher education: A scoping review of key characteristics and impact on academic performance and engagement. Heliyon, 10(21).
14. Erie, L. J. D. (2025). Learning Styles and Digital Competence of Senior High School Student in Filipino Subject.
15. Fadieieva, L. O. (2023). Adaptive learning: a cluster-based literature review (2011-2022). Educational Technology Quarterly, 2023, 319–366. https://doi.org/10.55056/etq.613

16. Fajarwati, A., Mendes, C., & Lima, R. (2026). COGNITIVE STYLES AND THEIR INFLUENCE ON LEARNING PREFERENCES IN EARLY CHILDHOOD EDUCATION. Research Psychologie, Orientation et Conseil, 3(1), 54-67.
17. Gaisey, I. K., Ntroaduro, A., Peasah, B. S. O., Anane, C., Oduro, T., & Attila, F. L. (2024). Gender differences on the effects of learning environments on academic performance among tertiary students. Education & Youth Research, 4(2), 130-139.
18. Gligorea, I., Cioca, M., Oancea, R., Gorski, A.-T., Gorski, H., & Tudorache, P. (2023). Adaptive Learning Using Artificial Intelligence in e-Learning: A Literature Review. Education Sciences, 13(12), 1216. https://doi.org/10.3390/educsci13121216
19. Gómez-Tabares, A. S., Marín, J. P. C., Vanegas, A. M., Martínez, D. A. L., & Gallego, E. M. M. (2022). The effect of coping strategies on the risk for suicidal ideation and behavior in adolescents. Mediterranean Journal of Clinical Psychology, 10(2), 2282-1619.
20. Hwang, G.-J., Sung, H.-Y., Hung, C.-M., & Huang, I. (2013). A learning style perspective to investigate the necessity of developing adaptive learning systems. Journal of Educational Technology & Society, 16(2), 188–197.
21. Jaya, A., Hartono, R., Wahyuni, S., & Yulianto, H. J. (2025). The Power of Collaborative Learning: How Peer Interaction Improves Student Learning Outcomes?. Journal of Education and Applied Teaching (JEAT), 1(1), 1-10.
22. Liyanage, M. P. P., Gunawardena, K., & Hirakawa, M. (2014). Using learning styles to enhance learning management systems. International Journal on Advances in ICT for Emerging Regions (ICTer), 7(1), 12–22.
23. Mahilum, D. Z. E., & Escarlos, G. S. (2025). Sociocultural Theory in the 21st-Century Philippine Secondary Classroom: A Systematic Review of Collaborative Learning and Student Achievement. International Journal of Research and Innovation in Social Science (IJRISS), 9(26).
24. Mariya, C. G., Joseph, A., Marina, A., Jesly, M. K., Veronica, M., & Sabeena, M. T. P. (2023). Study on Satisfaction of Students Regarding Online Classes in a Selected College of Nursing, Mangalore. Journal of Health and Allied Sciences NU, 13(02), 193-198.
25. Montecalvo, E. B. (2026). Analysis of Psychological Preparedness of Immersive Learning Experience to Math Learners. International Journal of Special Education, 41(3s), 117-143.
26. Özkır, B., & Eskici, M. (2023). Examination of the Relationship Between Academicians' Life Long Learning Tendencies and Thinking Styles. Journal of Teacher Education and Lifelong Learning, 5(2), 933-954.
27. Paris, S. (2025). TEACHERS'COLLABORATIVE PRACTICES, INNOVATIVENESS AND CREATIVITY. INTERNATIONAL MULTIDISCIPLINARY RESEARCH JOURNAL Учредители: International Organization of Educators and Researchers Inc., 6(4).
28. Paypa, J. A., Miranda, P. M. R., & Emperador, E. A. (2024). Learning style and reading performance of Grade 8 students. International Journal of Science and Management Studies, 7(1), 149-155.
29. Popescu, E., Bădică, C., & Moraret, L. (2010). Accommodating learning styles in an adaptive educational system. Informatica, 34(4), 451–462.
30. Putri, K. (2025). Implementing a Differentiation Approach in Teaching to Accommodate Diverse Learning Styles Of Primary School Students: A Systematic Literature Review. Journal for Lesson and Learning Studies, 8(1), 119-128.
31. Ramadani, F., & Inayati, N. L. (2024). Differentiated Learning in Islamic Religious Education: Solutions for the Diversity of Student Learning Styles. Ta'dib: Jurnal Pendidikan Islam, 29(2), 290-302.
32. Ramirez, A. D., Aparente, A. C., Cervantes, J. D., Toldo, L. G., Buo, M. G., Guma, M. J., ... & Recto, O. S. (2025). Assessing the Learning Style of Senior High School TVL Students Using the Grasha Riechmann Model. International Journal of Research and Innovation in Social Science (IJRISS), 9(11).
33. Shala, D. S., Thaçi, E., & Shala, A. (2024). Learning styles and motivation: their role in academic performance. Journal of Educational and Social Research, 14(3).
34. Sim, S. H., & Mohd Matore, M. E. E. (2022). The relationship of Grasha–Riechmann teaching styles with teaching experience of National-Type Chinese primary schools mathematics teacher. Frontiers in psychology, 13, 1028145.
35. Truong, H. M. (2016). Integrating learning styles and adaptive e-learning system: Current developments, problems and opportunities. Computers in Human Behavior, 55, 1185–1193. https://doi.org/10.1016/j.chb.2015.02.014
36. Wahyuni, A. S., Hani, H., Nurjanah, N., Utami, N. M., & Hakim, L. N. (2025). Gender and Learning Styles: A Correlational Study of Preferences Among English Education Students in Universities. Journal of Applied Linguistics (ALTICS), 7(1), 24-33.
37. Wanmei, W. (2025). Assessing the effect of a flipped classroom on students' learning performance. International Journal of Education and Practice, 13(1), 361–404. https://doi.org/10.18488/61.v13i1.4062
38. Wiangga, I. A. (2024). The impact of educators' teaching styles on secondary school learners' motivation in English. Journal of Educational Management and Strategy, 3(2), 136-144.