TPM Vol. 32, No. S8, 2025
ISSN: 1972-6325
https://www.tpmap.org/

THE RELATIONSHIP BETWEEN LEARNING STYLES AND ACADEMIC PERFORMANCE AMONG UNIVERSITY STUDENTS: A STUDY OF AMERICAN DEGREE TRANSFER PROGRAM STUDENTS IN STEM AND NON-STEM MAJORS USING VERMUNT'S INVENTORY LEARNING STYLES (ILS)

LIM YOU PING[1], LOH KAH HENG[2], THERESA CHIEW GIM EAN[3], TEH E-YANG[4], NG ENG HUI[5], YAP JIA HUI[6]

[1, 2, 3, 5] SCHOOL OF LIBERAL ARTS AND SCIENCES, FACULTY OF SOCIAL SCIENCE AND LEISURE MANAGEMENT, TAYLOR'S UNIVERSITY, MALAYSIA
[4] CARECLINICS EXCHANGE 106, MALAYSIA
[6] SCHOOL OF BUSINESS AND ECONOMICS, UNIVERSITI PUTRA MALAYSIA
EMAILS: [1*]YouPing.Lim@taylors.edu.my; [2] KahHeng.Loh@taylors.edu; [3] Theresa.Chiew@taylors.edu.my; [4] eyangteh@gmail.com; [5] EngHui.Ng@taylors.edu.my; [6] jiahuiyap@hotmail.com

Abstract— Globalization and increased mobility in higher education have diversified the student demographics, learning expectations and preferences, thereby influencing their academic performance, motivation, and career readiness. Divergent cognitive and academic demands in STEM and non-STEM fields further shape students' engagement and learning approaches. As traditional pedagogy is ineffective to address diverse needs, responsive teaching is vital to enhance learning outcomes. However, there is notable lack of research that simultaneously explores the diverse learning styles across multiple disciplines, highlighting the need to examine learning styles and correlation with academic performance in STEM and non-STEM contexts. This study employs the widely recognized Vermunt's Inventory Learning Styles (ILS) model as a guiding framework. By identifying and addressing learning styles, educators can design more inclusive teaching strategies in shaping a student educational journey and foster long-term broader development in a diverse and interdisciplinary university settings. Statistical results reveal no significant differences in the four core learning dimensions: process strategies, regulation strategies, learning orientations and mental model of learning across academic disciplines. However, STEM students scored significantly higher in the directed learning sub-components: deep processing, self-regulation and constructivist view. Statistical results showed a significant difference in the high adaptiveness sub-category: meaning-directed learning style. Correlation analysis showed no significant positive relationship between CGPA and learning styles among STEM and non-STEM students. Overall, the data supports the research outcome that learning environments can influence style development, and that promoting meaning-directed strategies across all disciplines could enhance academic engagement and performance.
Keywords - academic disciplines, academic performance, directedness of learning patterns, Inventory Learning Styles, learning adaptiveness.

I. INTRODUCTION

As global environment changes, educational goals must also change so as to prepare and equip students with 21st century competencies to ensure competitiveness and sustainability in a dynamic workplace. Traditional teaching pedagogy lacks real-world experiences to prepare graduates for work readiness skills required in the new competitive global environment. Readiness to embrace new experiences and challenges, willingness to acquire new knowledge and ability to apply new knowledge in life, workplace and academic are essential competencies that are in-demand by future job landscape [10].
Globalization and increased mobility in higher education have further diversified the demographic of its students with the emergence of students of different nationalities, cultural backgrounds, their learning expectations and ways of adopting and processing information. Students respond to different preferences and ways of learning that influence their academic performance and preparedness for progression and employment. Academic disciplines of STEM and non-STEM require different cognitive skills and academic demands which shape students' motivation, engagement in studies and plan for life beyond graduation [4]. Conventional one-size-fits-all pedagogy is ineffective to address the diverse students' learning styles [2]. Responsive and style-sensitive instruction can enhance learning experiences so as to promote academic performance and hence foster lifelong

learning. Consequently, there is a powerful force driving higher education systems to employ a variety of teaching strategies to support diverse cohorts to foster deep learning and strong academic performance [1].
In this rapidly evolving global environment and educational landscape, understanding students' learning style has become increasingly essential to ensure academic success, personal development and long-term professional development. Educators in higher education have continuously researched the best teaching pedagogies and strategies for improving students' academic outcomes and developing students with 21st century competencies [2], [20]. With the growing diversity in academic disciplines, it has become increasingly essential to study students in different academic backgrounds - STEM (Science, Technology, Engineering, and Mathematics) and non-STEM (Business and Liberal Arts) – their learning styles that may in turn influence their academic performance and broader development [9], [19]. However, there is lack of research when considering the diversity of learning styles across academic disciplines – particularly STEM and non-STEM fields. Therefore, it is timely and important for this study to identify learning styles in specific academic streams and examine how learning styles correlate with academic performance across academic disciplines. This study employs the widely recognized Vermunt's Inventory Learning Styles (ILS) model as a guiding framework to examine the learning styles - process strategies, regulation strategies, learning orientations and mental model of learning among American Degree Transfer Program (ADTP) students in STEM and non-STEM majors [19]. By identifying and addressing learning styles, educators can design more inclusive teaching strategies in shaping students' educational journeys and foster long-term broader development in a diverse and interdisciplinary university settings.

II. LITERATURE REVIEW

Over decades, learning has been defined by psychologists as a process of behavioral modification resulting from past experiences and environmental interactions [16]. Schneider employed constructive analysis to review the concept of learning from the disciplines of psychology, educational science, and philosophy [16]. She critically reconceptualize learning as the acquisition of knowledge by reasoning. Intentional change in cognitive framework influencing the learners' behavior and the application of knowledge in diverse situations.
Amoah's framework highlights that learning is a fundamental human cognitive function that facilitates innovation and self-improvement through experiences [3]. It is one of the most powerful features of human life and development. Learning helps to acquire new information and ideas, to organize and retain our memory. Through learning mechanism, it facilitates learners to retrieve and apply information over time for personal development, problem solving, and decision making.
Kolb's Learning Style Inventory (LSI) is grounded by his Experiential Learning Theory which emphasized that learning is best conceived as a process, not items of outcomes [9]. Kolb's learning model is conceptualized as a comprehensive and integrative mechanism of adaptation to the world and whereby knowledge is created through transformation of experience. According to Kolb's LSI model, the learning effectiveness is facilitated through the integration of four-stage cycle: concrete experience (feeling), abstract conceptualization (thinking), reflective observation (watching) and active experimentation (doing) to form the basis of an individual's learning style. In line with the basis of individual's learning styles, Kolb's classify learners into four distinct learning style categories: Diverging (feel and watch), Assimilating (think and watch), Converging (think and do) and Accommodating (feel and do). The LSI model assists learners to gain insight into their preferred learning stages and helps learners to develop skills across their learning cycle. Kolb's LSI model is also instrumental in guiding educators to construct instructional designs to tailor teaching strategies according to students' learning styles.
Neil Fleming is an educational developer from New Zealand who is known worldwide for developing the VARK model to assist individuals to realize their preferred learning styles for optimal learning outcomes [5]. Fleming categorized individuals preferred mode of learning, modality preferences, into four main styles: Visual, Aural, Read/write and Kinesthetic. The VARK model is a catalyst for educational development to align diverse learning and teaching strategies with the individual's learning preferences. Well-matched learning strategies with one's modal preferences are crucial to stimulate effective metacognition, foster deep learning and leads to improved learning outcomes.
Zajacova's affirmed Fleming's VARK model in the categories of Visual, Aural and Kinesthetic but modified Read/write to Tactile. Zajacova refers learning styles as individual approaches to perceiving and processing information, which are mainly classified into four modalities (VAKT) – Visual, Auditory, Kinesthetic, and Tactile learning [24]. Different groups of learners demonstrate diverse modality preferences throughout their learning process. Visual learners effectively acquire knowledge through written texts, diagrams and images, while auditory learners prefer listening to lectures and class discussions. Kinesthetic learners engage physical movement and active participation in their learning process, whereas tactile learners demonstrate optimal learning outcomes by touching and building objects, manipulating learning materials when engaging in the learning activities. Therefore, diversity of teaching approaches and well-matched activities with students' learning styles is vital to promote a stimulating and engaging learning environment for optimal learning outcomes.
Vermunt's Inventory Learning Styles (ILS) is recognized as one of the most influential models to conceptualize how students engage in learning. This model categorizes learning into four core components: processing strategies, regulation strategies, learning orientations, and mental learning models [19].

1. Processing strategies are thinking activities and focus on how students learn and process information. These strategies include deep processing (meaning-oriented learning), stepwise processing (reproduction-oriented learning), concrete processing (application-oriented learning), and passive processing (undirected learning).
2. Regulation strategies assess students' activities to regulate and control the processing strategies. These strategies are classified as self-regulation (autonomous planning, monitoring, and self-adjust learning), external regulation (relying on structured guidance like instructors or curricula), and lack of regulation (undirected learning).
3. Learning orientations refer to students' enjoyment of learning, motivation and conceptions of learning. The three scales are intrinsic motivation (personal interest in learning), extrinsic motivation (goal-oriented learning), and ambivalent motivation (lack of direction in learning).
4. Mental models of learning assess students' views and beliefs in active learning, constructing knowledge and self-discovery. There are four views of beliefs about learning: constructivist view (active engagement in learning), reproductive view (memorization and reproduction of knowledge), pragmatic view (application-based learning), and undirected view (unstructured and uncertain learning beliefs).

Vermunt's research finding asserted that students who exhibited strong self-directed learning tended to engage more in deep and concrete processing information. However, undirected learners were more inclined to rely on surface or stepwise processing strategies. The study also discovered that learning orientations and mental learning indirectly influence learners' regulation strategies which further impacted their processing strategies.

Prior research findings reinforce Vermunt's Inventory Learning Styles model by demonstrating that directed learning learners appeared more resilient and forceful when coping with stress. Through effective coping strategies and resources, directed learning learners demonstrate academic success [8], [11], [21]. Conversely, undirected learning learners are actively associated with higher stress and strain and report fewer coping mechanisms. An undirected learning approaches associations with ineffective coping strategies has been identified as a significant risk factor contributing to poor academic performance.

In contrast, research findings by Ab Manan, and Mohd Isa revealed no significant associations between learning styles preference and academic achievement in English language diploma students and the final year accounting students in UiTM Malaysia [1], [12]. The study by Hashim also reveals that preferred learning styles do not predict academic success among STEM students [7]. Similarly, several studies on STEM education (nursing education in virtual settings, medical program and science studies) found that there is no significant correlation between learning styles and academic performance [2], [6]. The studies conclude that students' personality, motivation, learning environments, psychological well-being and many other factors together shape academic outcomes. They highlighted that learner-driven factors such as motivation, self-regulation and engagement are regarded as key drivers to consistent academic success.

Despite differing findings on statistical significance between learning styles and academic performance, the evidence presented by various prior studies affirms Vermunt's view that educators should identify learner's learning styles and to redesign curricula and assessments in pursuit of the more effective educational outcomes [1], [8], [10], [11], [12], [20], [21]. Other domains, such as personal and cultural factors, academic environments and discipline-specific demands (STEM and non-STEM); epistemic tendencies of learners and their psychological well-being are driven factors to shape and support learning approaches and should also be addressed [8], [10], [20], [23]. Hence, optimal alignment between teaching strategies and learning styles with the specific domains will substantially foster meaningful and sustainable learning, enhance retention, stimulate motivation, improve student engagement and strengthen learners' academic success.

Interestingly, several prior research findings reveal that STEM and non-STEM students displayed multimodal learning preferences, with a combination of two or more learning preferences, indicating that they do not rely on a single dominant style [6], [13], [14], [15], [22]. The diverse learners employ flexibility and adaptability to process and retain information and demonstrate improved engagement, fostering cognitive development leading to academic success. Crucially, the authors advocate for pedagogical reforms and paradigm shifts towards a more dynamic and diversity in teaching and learning approaches. Embedding student-centered learning and experiential learning in complex educational settings are key success factors to cater to diverse learning needs, support deeper engagement and foster motivation that will ultimately improve learning outcomes in STEM and non-STEM studies.

III. Research Design And Framework

A. Problem Statement

Higher education educators continuously study and adopt the best teaching pedagogies and strategies to improve students' academic outcomes but fail to consider the diversity of learning styles across academic disciplines. The American Degree Transfer Program (ADTP) at Taylor's University comprises of students from wide range of majors in the STEM and non-STEM fields. While the students are often taught using similar instructional approaches, their cognitive preferences and learning strategies may differ significantly, thus potentially influencing their academic performance.

Prior research has shown that aligning teaching methods with students' preferred learning styles can enhance motivation, engagement, and academic performance. However, in Malaysia, particularly within the ADTP settings, there has been limited studies in examining how learning styles correlate with academic performance across different disciplines. There is also lack of empirical evidence using standardized learning style inventories such as the Vermunt's Inventory of Learning Styles (ILS) when assessing these relationships in multinational education environments.

This study seeks to address the gap by investigating the relationship between learning styles and academic performance among ADTP students in STEM and non-STEM majors. By identifying which learning styles are more prevalent in specific academic streams, and whether they correlate with academic success, this study aims to inform teaching practices that are more responsive to learner diversity. The findings from this study will offer insights for educators, program coordinators, and curriculum designers seeking to enhance learning outcomes in diverse and interdisciplinary university settings.

B. Purpose of study

Vermunt's Inventory Learning Style model is widely employed in empirical studies within single disciplines such as engineering, medicines, nursing, law, humanities and educational science. However, there is a lack of studies explicitly comparing STEM and non-STEM students using Vermunt's Inventory Learning Styles model. This study aims to close the gap by simultaneously examining the difference in learning style preferences in cross-disciplinary study between STEM and non-STEM students. This study also aims to examine how learning styles correlate with academic performance across academic disciplines.

Four null hypotheses and their subsidiary null hypotheses were formulated to shape and guide the study of learning styles in cross-disciplinary settings.

H_{01}: There is no significant difference in the learning style preferences between STEM and non-STEM students.

H_{01a}: There is no significant difference in the learning style between STEM and non-STEM students in the dimension of processing strategies.

H_{01b}: There is no significant difference in the learning style between STEM and non-STEM students in the dimension of regulation strategies.

H_{01c}: There is no significant difference in the learning style between STEM and non-STEM students in the dimension of learning orientation.

H_{01d}: There is no significant difference in the learning style between STEM and non-STEM students in the dimension of mental models of learning.

H_{02}: There is no significant difference in the directedness of learning patterns between STEM and non-STEM students.

H_{03}: There is no significant difference in the learning adaptiveness between STEM and non-STEM students.

H_{04}: There is no significant relationship between learning styles and academic performance among STEM and non-STEM students.

H_{04a}: There is no significant relationship between learning styles and academic performance among STEM students.

H_{04b}: There is no significant relationship between learning styles and academic performance among non-STEM students.

C. Research Framework

This study uses the widely recognized Vermunt's Inventory Learning Styles (ILS) model as a guiding framework to examine the learning styles - process strategies, regulation strategies, learning orientations and mental model of learning [17], [18]. These four core components of learning styles are interconnected and each influencing the other. Effective process strategies promote strong regulation strategies, and in turn enhance the effectiveness of learners' process and engage learning materials. Learning orientations are influenced by learners' regulation strategies and correspondently learners' motivation affects how learners regulate their learning. Learning orientation shape learners' mental models and reciprocally the beliefs about learning reinforce learner's motivation and conceptions of learning.

This study focuses on two core dimensions of Vermunt's Inventory Learning Styles: directedness of learning patterns and learning adaptiveness. As depicted in Figure 1, directed learning styles demonstrate goal-driven and capability in adapting effective learning strategies. Learners actively engage in purposeful, structured, intentional, self or external regulated approaches to learning. In contrast, undirected learners are confused and uncertain of their motive for learning. They are typically low in persistence, lack control, structure, direction, motivation and encounter ineffective learning approaches.

The central idea of Vermunt's Inventory Learning Styles model is the dimension of learning adaptiveness as depicted in Figure 1. The level of learning adaptiveness assesses learner's effectiveness to adjust their learning strategies in diverse academic environments and domain-specific requirements. Meaning-directed learning style is the most adaptive and effective learning style. This is typically characterized by deep processing, self-regulated learning, intrinsic motivation and active engagement in learning. Application-directed learning style is regarded as moderately adaptive. Learners focused on practical and application-based learning but driven by extrinsic motivation associated with grades, rewards, and career goals. In contrast, reproductive-directed learning is considered less effective and is associated with rigid study strategies. These learners typically rely on rote memorization, reproduction of knowledge, prefer direct and structured external guidance, and lack clear motivation for learning. Undirected learning reflects least adaptive and is often associated with confusion, uncertainty and disorganization. These characteristics lead to low motivation, lack of meaningful goals and ineffective learning strategies.

FIGURE 1: VERMUNT'S INVENTORY LEARNING STYLES: DIRECTED/UNDIRECTED LEARNING STYLES AND LEARNING ADAPTIVENESS

Vermunt's Learning Styles model provides a valuable lens for this study to examine the learning styles in the two dimensions: directedness of leaning patterns and learning adaptiveness among STEM and non-STEM students. The findings will offer insights for educators to design effective pedagogical approaches to foster better student engagement and enhance learning outcomes in a diverse educational environment.

IV. METHODOLOGY

This study simultaneously explores the diversity of learning styles and academic performance across multiple academic fields – particularly STEM (Science, Technology, Engineering, and Mathematics) and non-STEM (Business and Liberal Arts) fields. This study employs Vermunt's Inventory Learning Styles (ILS) model as a guiding framework to examine the learning styles - process strategies, regulation strategies, learning orientations and mental model of learning among American Degree Transfer Program (ADTP) students in STEM and non-STEM major.

This study focuses on two core dimensions, directedness and adaptiveness of Vermunt's Inventory Learning Styles. As illustrated in Figure 1, the sub-components within each learning style category are organized into two classifications: directed and undirected learning styles. These classifications allow more systematic comparison between STEM and non-STEM with respect to learner's information processing strategies, motivation and conceptions of learning, regulation strategies in the learning process, and engagement in learning activities.

The sub-components of Vermunt's Inventory Learning Styles are grouped according to their level of learning adaptiveness as illustrated in Figure 1. Meaning-directed learning styles include sub-components of deep processing, self-regulation, intrinsic motivation and constructivist view of learning are considered the most adaptive and effective learning style. Application-directed learning style composing of the sub-components of concrete processing, extrinsic motivation and pragmatic view are regarded as moderate adaptive and practical learning style. In contrast, the low adaptive and less effective reproductive-directed learning style consists of stepwise processing, external regulation, ambivalent motivation and reproductive view of learning. Undirected learning style is least adaptive with passive processing along with lack of regulation and undirected view of learning and is often associated with poor academic outcomes. These groupings enable the systematic comparison of the adaptiveness of learning approaches among STEM and non-STEM students to support the discipline-specific learning needs.

The data collected was based on Vermunt's scoring key for the Inventory Learning Styles in higher education [17]. In addition to learning style data, participants' Cumulative Grade Point Average (CGPA) were obtained to serve as an indicator of academic performance. Respondents' CGPA data were retrieved from Taylor's University's Campus Management System (CMS) to ensure the accuracy of the academic performance data. A total of 100 participants responded to the online questionnaire. The respondents comprised of both local Malaysian students and international students from various countries (Southeast Asia, East Asia, South Asia, Africa and Europe) studying in the Taylor's American Degree Transfer Program. The sample included male and female students across different academic disciplines, grouped into two categories: STEM (Science, Technology, Engineering, and Mathematics) and non-STEM (Business and Liberal Arts) fields. Total of fifty-six percent of respondents major in STEM and forty-four percent are from non-STEM fields.

All items in the online questionnaire were responded to a Likert scale of 1-5, where 1 = Strongly Disagree and 5 = Strongly Agree. The data were tabulated, converted into CVS and analyzed using SPSS version 29. The analysis addressed four main null hypotheses and their subsidiary null hypotheses with regards to differences in learning styles between STEM and non-STEM students, as well as analysis in the dimensions of directedness of learning patterns and learning adaptiveness.

The correlations between learning styles and academic performance were also examined in the statistical analysis.

1. Independent samples t-tests were used to examine if there are significant differences in learning style preferences between STEM and non-STEM students in the four dimensions: processing strategies, regulation strategies, learning orientation and mental models of learning.
2. Independent samples t-tests were used to examine if there are significant differences in the directedness of learning patterns and learning adaptiveness between STEM and non-STEM students.
3. Pearson correlation coefficients were calculated to assess the relationship between learning styles and academic performance among STEM students as well as among non-STEM students.
4. The statistical significance level was set at $p < 0.05$.

V. RESULTS

A. Testing of Null Hypotheses 1 and its subsidiaries

The results from the independent t-tests are presented in Table I. Results indicated that there is no statistically significant difference in the four learning style dimensions between STEM and non-STEM students. Null hypothesis H_{01} and all its subsidiaries (H_{01a} – H_{01d}) failed to be rejected ($p > 0.05$). This suggests that overall learning style preferences are not discipline-specific in this sample.

TABLE I: STEM AND NON-STEM VS LEARNING STYLES MAIN DIMENSIONS

Main Dimension	STEM Mean	Non-STEM Mean	t	p-value	Significance
OVERALL	3.6194	3.5625	0.528	0.599	No
Processing strategies	3.6598	3.5267	1.255	0.213	No
Regulation strategies	3.6321	3.5129	0.960	0.339	No
Learning Orientation	3.6482	3.6795	-0.250	0.803	No
Mental Models	3.5375	3.5307	0.057	0.954	No

B. Testing of Null Hypotheses 2

The results from the independent t-tests are presented in Table II(A) and (B). While results indicated that there is no statistically significant difference in the directedness of learning patterns between STEM and non-STEM students as reflected in Table II(A), null hypothesis H_{02} failed to be rejected ($p > 0.05$), results tabled and reflected in Table 2(B), indicated that when the 14 Inventory Learning Styles subcomponents were analyzed, STEM students scored significantly higher in three key directed learning patterns sub-components: Deep Processing ($t=2.26$, $p=0.03$), Self-Regulation ($t=2.25$, $p=0.03$), Constructivist View ($t=2.02$, $p=0.05$). No significant differences were found in the other remaining sub-components.

TABLE II(A): STEM AND NON-STEM VS DIRECTEDNESS OF LEARNING PATTERNS MAIN DIMENSIONS

Main Dimension	STEM Mean	Non-STEM Mean	t	p-value	Significance
OVERALL	3.8676	3.7075	1.379	0.171	No
Processing strategies	3.8226	3.6288	1.681	0.096	No
Regulation strategies	3.9259	3.6784	1.899	0.061	No
Learning Orientation	3.9455	3.8500	0.706	0.482	No
Mental Models	3.7762	3.6727	0.803	0.424	No

TABLE II(B): STEM AND NON-STEM VS DIRECTEDNESS OF LEARNING PATTERNS SUB-COMPONENTS

Sub-components	Style	STEM Mean	Non-STEM Mean	t	p-value	Significance
OVERALL		3.8676	3.7075	1.379	0.171	No
Deep processing	Directed	4.0643	3.7409	2.259	0.026	**Yes**
Stepwise processing	Directed	3.4107	3.3432	0.464	0.644	No
Concrete processing	Directed	3.9929	3.8023	1.178	0.242	No
Passive processing	Undirected	3.1714	3.2205	-0.301	0.764	No
Self-regulation	Directed	3.8911	3.5750	2.245	0.027	**Yes**

External regulation	Directed	3.9607	3.7818	1.251	0.214	No
Lack of regulation	Undirected	3.0446	3.1818	-0.781	0.218	No
Intrinsic motivation	Directed	3.8857	3.7114	1.235	0.220	No
Extrinsic motivation	Directed	4.0054	3.9886	0.114	0.910	No
Ambivalent motivation	Undirected	3.0536	3.3386	-1.700	0.092	No
Constructivist view	Directed	3.8429	3.5500	2.019	0.046	**Yes**
Reproductive view	Directed	3.6857	3.6318	0.388	0.699	No
Pragmatic view	Directed	3.8000	3.8364	-0.220	0.826	No
Undirected view	Undirected	2.8214	3.1045	-1.373	0,173	No

C. Testing of Null Hypotheses 3

The results from the independent t-tests are presented in Table III. Results indicated that there is no statistically significant difference in the learning adaptiveness between STEM and non-STEM students as reflected in Table III, null hypothesis H_{03} failed to be rejected ($p > 0.05$). However, there is significant difference in the high learning adaptiveness between STEM and non-STEM students (t=2.197, p=0.30). Meaning-directed learning styles include sub-components of deep processing, self-regulation, intrinsic motivation and constructivist view of learning are considered the most adaptive and effective learning style. No significant differences were found in moderate learning adaptiveness (application-directed learning style), low learning adaptiveness (reproductive-directed learning style), and very low learning adaptiveness (undirected learning style).

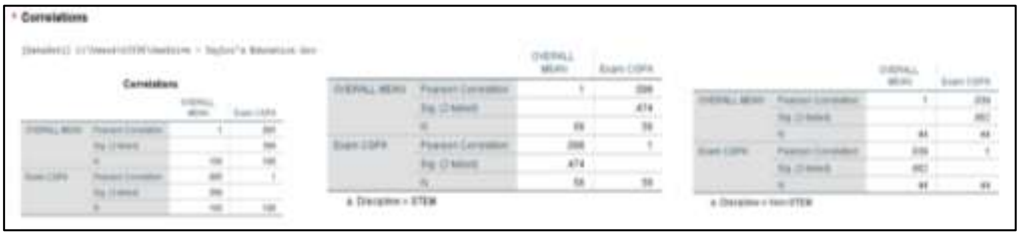
TABLE III: STEM AND NON-STEM VS ADAPTIVENESS

Learning Style Category	Adaptiveness	t (df)	p-value (2-tailed)	Significant?	Mean Difference	95% CI
OVERALL MEAN		0.503 (98)	0.616	No	0.057	[−0.168, 0.282]
Meaning-Directed: Deep processing, Self-regulation, Intrinsic motivation, Constructivist view	**High**	**2.197 (94)**	**0.030**	Yes	0.277	[0.027, 0.527]
Application-Directed: Concrete processing, Extrinsic motivation, Pragmatic view	Moderate	0.423 (93)	0.673	No	0.057	[−0.210, 0.324]
Reproduction-Directed: Stepwise processing, External regulation, Ambivalent motivation, Reproductive view	Low	0.033 (95)	0.974	No	0.004	[−0.225, 0.233]
Undirected: Passive processing, Lack of regulation, Undirected view	Very Low	−0.979 (93)	0.330	No	−0.156	[−0.474, 0.161]

D. Testing of Null Hypotheses 4 and its subsidiaries

The results from the Pearson product-moment correlation are presented in Table IV. Results indicated that null hypothesis H_{04} and all its subsidiaries (H_{04a} – H_{04b}) failed to be rejected and that there is no significant relationship between learning styles and academic performance among STEM and non-STEM students (r(100)=0.09, p=0.40, two-tailed). When compared among STEM students alone as well as non-STEM students alone, there was also no significant relationship between their learning styles and academic performance (r(56)=0.10, p=0.47, two-tailed; r(44)=0.04, p=0.80, two-tailed).

TABLE IV: PEARSON'S PRODUCT-MOMENT CORRELATION COEFFICIENT BETWEEN LEARNING STYLES AND ACADEMIC PERFORMANCE AMONG STEM AND NON-STEM STUDENTS



VI. DISCUSSION AND CONCLUSION

Statistical results comparing STEM and non-STEM students reveal no significant differences in the four core learning dimensions: process strategies, regulation strategies, learning orientations and mental model of learning. This suggests that overall learning style preferences are not discipline-specific in this sample. This result is parallel to several prior research which reported that STEM or non-STEM students displayed multimodal learning preferences, with a combination of two or more learning preferences, and they do not rely on a single dominant style [6], [13], [14], [15], [22]. This is also consistent with a study by Yu et al. which concludes that learning environments significantly shape and support learning approaches [23].

However, results from this study found that STEM students scored significantly higher in the three key directed learning sub-components: deep processing, self-regulation and constructivist view. Statistical results also showed a significant difference in the high adaptiveness sub-category: meaning-directed learning style with a combination of deep processing, self-regulation, intrinsic motivation and a constructivist view. This signifies that STEM students have a greater tendency toward meaningful and autonomous learning strategies. This is in line with the nature of STEM curricula that is characterized as problem-based driven, conceptual application and experimentation which will naturally foster deeper engagement, self-regulation and promote intrinsic motivation in their learning setting. Conversely, the lack of significant difference in low learning adaptiveness (application or reproduction oriented learning style) indicates that these approaches are shaped more by institutional assessment structures than by academic disciplinary factors.

Correlation analysis showed no significant positive relationship between CGPA and learning styles among STEM and non-STEM students. This supports prior researchers who reported that learning styles preference do not predict academic success among STEM students [6], [7]. This implies that students' academic performance is influenced by a multitude of factors beyond learning style preferences. Students' personality, motivation, learning environments, psychological well-being and many other factors are regarded as key drivers for achieving consistent academic success.

In conclusion, this study further affirms that STEM or non-STEM students displayed multimodal learning preferences, with a combination of two or more learning preferences. Aggregate learning styles categorizations have limited direct value in predicting academic disciplinary learning preferences and academic performance. However, when examining specific sub-components within each learning style category such as deep processing, self-regulation, constructivist view and meaning-directed learning revealed discipline-specific differences. The data supports the research outcome that learning environments can influence style development, and that promoting meaning-directed strategies across all disciplines could enhance academic engagement and performance. Embedding student-centered learning and experiential learning in complex educational settings are key success factors when catering to diverse learning needs and will support deeper engagement and foster motivation that ultimately will improve learning outcomes in STEM and non-STEM studies. Future research should continue to explore the relationship among academic discipline, specific learning style sub-components and discipline-specific pedagogies, using cross-longitudinal data to track changes in students' learning patterns and their engagement with institutional practices over time.

REFERENCES

[1] Ab Manan, N. A., Yusof, J., & Azizan, N. (2024). The Relationship Between Learning Styles and English Language Achievement and Gender Among Diploma Students at A Public University in Malaysia. Journal of Creative Practices in Language Learning and Teaching, 12(1), 167–182.

[2] Al Najjar, B., & Zacharias, N. (2018). Investigating engineering student learning style trends by using multivariate statistical analysis. Education Sciences, 9(1), 58.

[3] Amoah, D. K. (2022). Advances in the understanding and enhancement of the human cognitive functions of learning and memory. Brain Science Advances, 8(4), 265–273.

[4] Entwistle, N. J., & Ramsden, P. (1983). Understanding student learning. Croom Helm.

[5] Fleming, N., and Baume, D. (2006) Learning Styles Again: VARKing up the right tree!, Educational Developments, SEDA Ltd, Issue 7.4, 7.

[6] Gayef, A., Çaylan, A., & Temiz, S. A. (2023). Learning styles of medical students and related factors. BMC Medical Education, 23, 282.

[7] Hashim, N. H. C., & Osman, K. (2025). Learning Styles and Academic Achievements of STEM Students. International Journal of Academic Research in Progressive Education and Development, 14(1), 287–301.

[8] Kimatian, S., Lloyd, S., Berger, J., Steiner, L., Mckay, R., Schwengel, D. (2017). Undirected learning styles and academic risk: Analysis of the impact of stress, strain and coping, Journal of Education in Perioperative Medicine, Volume XIX, Issue II.

[9] Kolb, D. (1984). Experiential Learning: Experience as the Source of Learning and Development. Englewood Cliffs, NJ: Prentice Hall.

[10] Lonka, K., Ketonen, E. and Vermunt, J.D. (2021). University students' epistemic profiles, conceptions of learning, and academic performance. Higher Education, April 2021, Vol. 81, No. 4, 775-793.

[11] Maya, J., Luesia, J. F., & Pérez Padilla, J. (2021). The Relationship between Learning Styles and Academic Performance: Consistency among Multiple Assessment Methods in Psychology and Education Students. Sustainability, 13(6), 3341.
[12] Mohd Isa, N. S., Omar, N., Mohd Fatzel, F. H., Ghazali, Z. M., & Anas, N. (2021). The relationship between students' learning styles and academic performance: Final-year accounting students. EJOSS Journal, 7(1), 1–9.
[13] 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, 11, 15–19.
[14] Nor Haliza Che Hashim, Kamisah Osman. (2025). Learning Styles and Academic Achievements of Stem Students, International Journal of Academic Research in Progressive Education and Development, Vol. 14 , No. 1, E-ISSN: 2226-6348.
[15] Norhayati binti Ishak, Mohd Mahzan Awang. (2017). The Relationship of Student Learning Styles and Achievement in History Subject, The International Journal of Social Sciences and Humanities Invention 4(3): 3372-3377.
[16] Schneider, K. (2024). What is learning? Psychology, 15(5), 779–799.
[17] Vermunt, J. D. (1994). Inventory of Learning Styles (ILS) in Higher Education; scoring key for the inventory of learning styles in higher education. Tilburg University, Department of Educational Psychology.
[18] Vermunt, J.D. (1996). Metacognitive, cognitive and affective aspects of learning styles and strategies: a phenomenographic analysis, Higher Education, 31 (1996), 25-50.
[19] Vermunt, J. D. (1998). The regulation of constructive learning processes. British Journal of Educational Psychology, 68(2), 149–171.
[20] Vermunt, J. D., Vermetten, Y. J., & Lodewijks, H. G. (2005). Relations between student learning patterns and personal and contextual factors and academic performance. Higher Education, 49, 205–234.
[21] Vermunt, J.D. and Vermetten, Y. J. (2004). Patterns in Student Learning: Relationships Between Learning Strategies, Conceptions of Learning, and Learning Orientations. Educational Psychology Review, Vol. 16, No. 4, Measuring Studying and Learning in Higher Education—Conceptual and Methodological Issues (2004), 359-384.
[22] Wu, C.-C., Wang, T.-H. (2025). What is the role of learning style preferences on the STEM learning attitudes among high school students? International Journal of Educational research 129, 102488.
[23] Yu, J., Vermunt, J. D., & Burke, C. (2021). Students' learning patterns and learning spaces in higher education: an empirical investigation in China. Higher Education Research & Development, 40(4), 868-883.
[24] Zajacova, B. (2013). Learning styles: An overview of concepts and research tools and introduction of our research design in physics education field. Proceedings of the 2013 Workshop on Data Science, 316–321. Charles University in Prague.