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Analyzing The Factors Affecting Learning Motivation and Academic Performance In Hybrid Learning Setup Among UST Engineering Students

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Abstract

Amid the COVID-19 pandemic, the Philippines shifted to distance learning, later transitioning to hybrid setups with limited face-to-face classes. At the University of Santo Tomas (UST), hybrid learning has become a permanent setup. As this offers flexibility, it also brings challenges to students, as highlighted by related studies. The goal of this study is to assess and analyze behavioral, physical, and macro-ergonomic factors influencing their learning motivation and academic performance. A total of 287 engineering students in UST, using purposive sampling, answered the questionnaire in an online administered survey. Behavioral and ergonomic factors were analyzed using the Partial Least Square-Structural Equation Model (PLS-SEM). Results showed that attendance, student-centered method of teaching, and use of learning management system positively influence learning motivation which positively impacts their academic performance. The findings imply that students, academic teachers, and school administrators should be aware of and apply behavioral, physical, and macro-ergonomic concepts to positively influence students' learning in a hybrid learning environment. As hybrid learning has become a norm in the university, it is essential that behavioral and ergonomic factors are considered to establish an effective learning system as it improves students' learning motivation and academic performance in a hybrid learning setup.

Keywords
hybrid learning setup, ergonomic factors, learning motivation, academic performance, PLS-SEM

1. Introduction

The COVID-19 pandemic has brought significant changes globally, impacting various sectors, including education. To address challenges in learning continuity, several countries, including the Philippines, adopted distance learning as the primary modality. In September 2021, former President Rodrigo Duterte approved the Commission on Higher Education's (CHED) request to expand limited face-to-face classes for selected programs, including Engineering and Technology in Higher Education Institutions (HEIs) (CHED 2021). This shift led to a transition from full-distance learning to a hybrid setup, which integrates both online and face-to-face instruction (Hentea et al. n.d.).

To standardize hybrid learning, CHED's 2022 Memorandum Order No. 16 mandated a 50:50 ratio for online and face-to-face instruction (The Flame News 2023). However, institutions like the University of Santo Tomas (UST) Faculty of Engineering implemented a 70:30 distribution, prioritizing in-person learning (The Varsitarian 2024). While hybrid learning offers flexibility, it presents challenges for students, including technological issues, distractions, lack of focus, fatigue, and low motivation (Khatun et al. 2022). The shift in learning modality has introduced new academic and behavioral adjustments that impact student performance.

Addressing these challenges requires an ergonomic approach to improve the learning experience. Physical ergonomics focuses on factors such as illumination, noise levels, temperature, and air quality, which affect student comfort and concentration (Gumasing et al. 2023). Meanwhile, macro-ergonomics examines broader system-level factors, including teaching delivery, study management, and the organization of hybrid learning environments (Panjaitan & Ali 2019; Gumasing and Castro 2023). Research indicates that physical wellness is a key motivator in hybrid learning, influencing students' engagement and academic performance (Istijanto 2019).

This study aims to assess how physical ergonomics and macro-ergonomic factors affect the learning motivation and academic performance of University of Santo Tomas engineering students. Using Structural Equation Modeling (SEM), a multivariate method for analyzing causal relationships (Fan et al. 2016), this research will quantify the impact of these ergonomic factors. The findings will provide valuable insights for students, educators, academic institutions, and parents in optimizing hybrid learning environments, enhancing student well-being, and improving academic outcomes.

1.1 Objectives

This study aims to determine and analyze the influence of physical and macro-ergonomic factors on learning motivation in a hybrid learning setup among engineering students. Additionally, it seeks to provide adequate information to students, parents/guardians, lecturers, and school administrators on how to effectively cope with the challenges of a hybrid learning environment. Specifically, it aims to determine whether behavioral factors (i.e., student workload and attendance), physical factors (i.e., noise, temperature, illumination, and air quality), and macro-ergonomic factors (i.e. student-centered teaching method, teacher-student interactive teaching method, and study management) impact engineering students' learning motivation in a hybrid learning setup. Lastly, the study aims to discover how learning motivation significantly affects the academic performance of engineering students.

2.Literature Review

While previous studies have extensively examined ergonomic and demographic factors separately, there is limited research integrating ergonomic, demographic, and behavioral factors to assess their combined influence on learning motivation and academic performance in hybrid learning environments. This study aims to fill this research gap by incorporating a comprehensive approach to evaluating how these factors interact, ultimately providing a holistic understanding of the challenges and opportunities faced by engineering students in a hybrid setup.

Demographic and behavioral factors, including age, gender, academic workload, and attendance, have been extensively studied. Bećirović and Bećirović (2017) found an inverse relationship between age and motivation, while Tabassum and Akhter (2020) confirmed that age significantly affects academic performance. Gender differences were observed, with female students generally outperforming males (Siddiky and Haque 2019). Additionally, academic workload negatively impacts intrinsic motivation, as an increased volume of tasks results in decreased motivation (Brubacher and Silinda 2019). Meanwhile, studies on attendance have produced mixed findings, with some suggesting a positive correlation between attendance and performance (Sekiwu et al. 2020) and others reporting a negative relationship (Ancheta et al. 2021).

Physical ergonomics plays a crucial role in students' cognitive performance and motivation. Noise exposure has been linked to psychological stress, reduced concentration, and impaired learning outcomes (Minichilli et al. 2018; Brink et al. 2020). High noise levels in classrooms can disrupt cognitive processes, leading to decreased academic performance (Swargiary 2023). Similarly, illumination affects students' engagement, with proper lighting improving focus and motivation, while inadequate lighting contributes to fatigue and eye strain (Soltaninejadet al. 2021; Gumasing et al. 2023). Temperature fluctuations also influence cognitive function, as extreme heat or cold conditions hinder students' ability to concentrate and retain information (Brink et al., 2020). Furthermore, poor air quality negatively impacts cognitive functions, motivation, and overall academic performance, emphasizing the need for adequate ventilation in learning environments (Wang et al. 2021).

Macro-ergonomic factors such as teaching delivery and study management significantly influence student motivation. Effective teaching methods contribute to higher engagement and improved learning outcomes, while poor instructional approaches can hinder motivation (Gumasing and Castro 2023; Isa et al. 2020). Instructors who employ interactive and student-centered teaching styles positively impact learning experiences. Additionally, the use of Learning Management Systems (LMS) has been shown to enhance student engagement and accessibility to learning materials (Ahmad et al. 2021; Ajijola et al. 2021). However, challenges such as limited instructor-student interaction and inadequate feedback have been identified as barriers to maximizing LMS effectiveness (Araka et al. 2021).

Hybrid learning, while offering flexibility, presents significant challenges, including technological constraints, limited engagement opportunities, and increased cognitive demands. Studies highlight the difficulty students face in maintaining motivation and focus due to the transition between online and face-to-face learning (Sulaiman et al. 2023). Additionally, students often struggle with time management and require strong support from instructors and parents to adapt effectively. Student engagement remains a concern, as research suggests that learners still prefer traditional in-person interactions over hybrid models (Gamage et al. 2022).

Learning motivation is a key determinant of academic success. Motivation drives students to engage in learning activities, set academic goals, and achieve better performance. Intrinsic motivation, which stems from personal interest and enjoyment, has been found to positively correlate with academic success (Muharam et al. 2019). The blended learning approach, which integrates online and face-to-face instruction, can enhance motivation by offering flexibility and interaction (Permata & Nanda 2021). However, external factors such as workload, classroom environment, and instructional strategies influence students' ability to stay motivated.

Academic performance is strongly linked to motivation, with higher motivation levels leading to improved learning outcomes. Studies indicate that motivation serves as a predictor of student success, influencing their ability to achieve high grades and perform well academically (Muhammad et al. 2021; Liu et al. 2022). Self-belief and learning strategies also play a significant role in academic achievement, as students with higher confidence levels tend to perform better in various subjects (Steinmayr et al. 2019). Furthermore, research suggests that both intrinsic and extrinsic motivation contribute to academic success, with intrinsic motivation being more influential in younger students and extrinsic motivation becoming increasingly significant as students mature (Liu et al. 2022).

Overall, the literature establishes that ergonomic, demographic, and behavioral factors are key determinants of students' learning motivation and academic performance in hybrid learning environments. Addressing these factors can enhance student engagement, optimize learning conditions, and improve academic outcomes. The findings emphasize the importance of ergonomic-friendly study spaces, effective teaching strategies, and institutional support to ensure a productive hybrid learning experience.

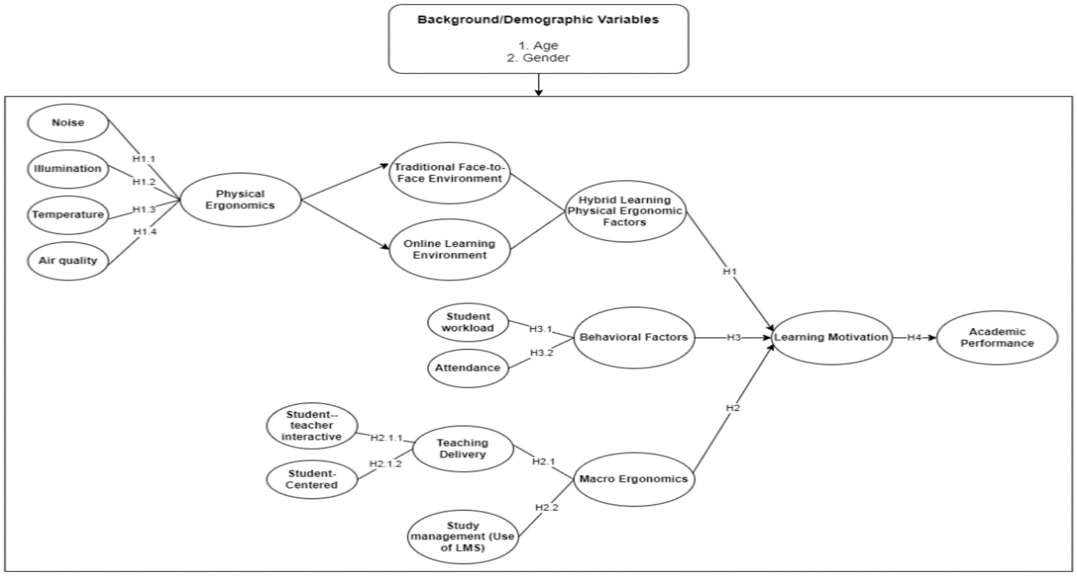

Figure 1. Conceptual Framework

The conceptual framework shown above discusses how the researchers will establish the relationship between the various factors (independent), such as physical ergonomics, macro ergonomics, and behavioral factors that affect the learning motivation of the University of Santo Tomas undergraduate engineering students. Eventually, the researchers will look into the relationship between learning motivation and the academic performance of the said students.

3. Methods

The researchers used Partial Least Squares-Structural Equation Modeling (PLS-SEM), a multivariate statistical approach that combines both multiple regression analysis and factor analysis to investigate complicated interactions between numerous independent and dependent variables (Hair et al. 2022). PLS-SEM was chosen for this study because of its capacity to handle complicated models with various components and indicators, focusing on several physical and macro ergonomic elements influencing learning motivation in a hybrid learning environment. Further, the researchers used R programming to perform data analysis using PLS-SEM.

Normally, to determine the minimum sample size in SEM is the “10-times rule”. The minimum sample size should be at least ten times the study’s number of indicators (Kock & Hadaya, 2018). In simulation studies, the minimum sample size recommendation is 100. The sample size for the academic studies concerning the academic performance and learning motivation of students that use PLS-SEM (Partial Least Square-Structural Equation Model) ranges from 100-300 (e.g., Huang, 2021; Gumasing & Castro, 2023). Adapting Gumasing & Castro’s (2023) study, UST undergraduate engineering students can be represented by 300 participants.

4.Data Collection

The data-collecting instrument used in this study was a survey questionnaire answered by the eligible respondents, UST Faculty of Engineering students, who responded based on their experiences and perceptions in a hybrid learning environment. The questionnaire was answered by utilizing online surveys through Google Forms. The data gathered was interpreted using statistical analysis through the Partial Least Squares-Structural Equation Modelling (PLS-SEM). The statistical tool helped the researchers determine the relationship between different factors that affect the learning motivation and academic performance of engineering students in a hybrid learning environment. From the sampling plan, the researchers targeted 300 participants based on department population percentages. A final sample of 287 respondents was obtained through purposive sampling technique.

5.Results and Discussion

5.1Estimation of the Path Model

Table 1. Impact of Behavioral Factors on the Learning Motivation of Engineering Students in a Hybrid Learning Setup - Full Model

Paths	**Estimate**	**Standard Error**	**z-value**	**p-value**
Learning Motivation				
Student Workload	0.120	0.066	1.824	0.068
Attendance	0.744	0.104	7.142	<0.001*

**Denotes significance at a 5% significance level*

The SEM regression results indicate a positive but marginally non-significant effect of workload on learning motivation (β = 0.120, p = 0.068), suggesting that while workload may influence motivation, the relationship is not statistically significant. The finding contrasts with Brubacher & Silinda's (2019) study, which found that academic workload negatively correlates with intrinsic motivation in a distance learning environment. Nicholls et al. (2022) further explored the impact of high academic demands on students' well-being through qualitative methods, highlighting how increased workloads affect students' motivation and psychological states.

On the contrary, the relationship between attendance and learning motivation was highly significant. The path coefficient for attendance on learning motivation was 0.744, with a p-value of less than 0.001. This indicates a strong and statistically significant positive effect, suggesting that increased attendance is strongly associated with higher levels of learning motivation. It was also seen in Sekiwu et al. (2020) study that there is a significant positive relationship between school attendance and academic performance among Universal Primary Education students in Uganda, reinforcing the role of attendance in student success.

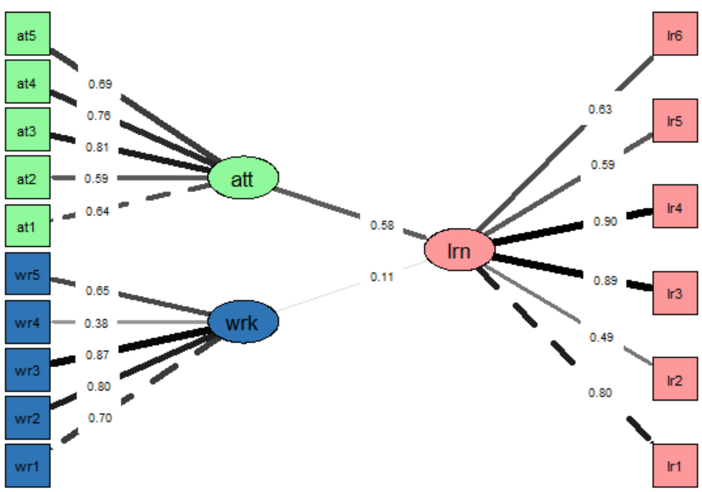

Figure 2. Path Diagram with Standardized Coefficients for the Model of the Behavioral Factors on the Learning Motivation of Engineering Students

Table 2. Impact of Physical Factors on the Learning Motivation of Engineering Students in a Hybrid Learning Setup - Full Model

Paths	**Estimate**	**Standard Error**	**z-value**	**p-value**

Learning Motivation				
Noise Online	-0.098	0.067	-1.474	0.140
Noise Onsite	0.162	0.068	2.380	0.017*
Illumination Online	0.040	0.097	0.413	0.680
Illumination Onsite	0.222	0.084	2.636	0.008*
Temperature Online	0.117	0.066	1.761	0.078
Temperature Onsite	0.462	0.088	5.233	< 0.001*
Air Quality Online	0.016	0.093	0.170	0.865
Air Quality Onsite	-0.086	0.090	-0.952	0.341

**Denotes significance at a 5% significance level*

The SEM results in Table 2 indicated that noise, illumination, and temperature in onsite classes significantly enhance learning motivation among engineering students in a hybrid setup. However, noise, illumination, temperature in online classes, and air quality in both learning environments did not show a significant impact, suggesting that other factors may influence learning motivation.

Noise in onsite classes had a statistically significant positive relationship with learning motivation (β = 0.162, p = 0.017), indicating that a comfortable noise level can contribute to higher motivation. This finding contrasts with existing literature, where Swargiary (2023) reported that high noise levels negatively impact cognitive performance, attention, and learning, while quieter environments promote focus and academic success. However, Braat-Eggen et al. (2021) suggested that noise sensitivity does not affect student performance, with realistic background noise having minimal impact on task completion. These mixed findings suggest that noise may have context-dependent effects, where moderate levels of ambient sound might create a more engaging and stimulating learning environment, while excessive noise remains a hindrance. Similarly, illumination in onsite classrooms showed a significant effect on learning motivation (β = 0.222, p = 0.008), meaning that well-lit learning spaces enhance students' motivation. Oselumese et al. (2016) supported this assumption, stating that classroom lighting influences motivation and academic performance.

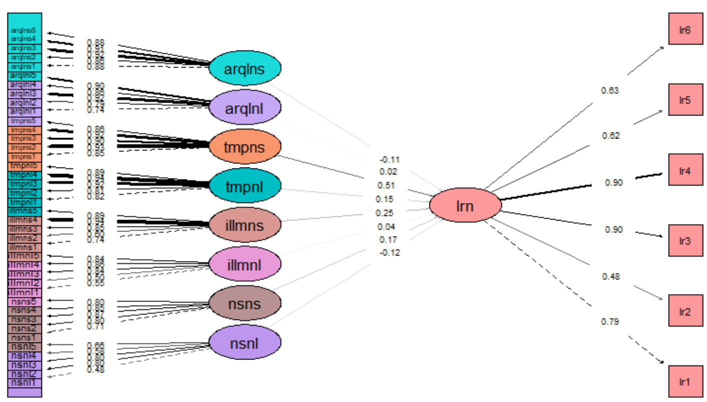

Figure 3. Path Diagram with Standardized Coefficients for the Model of the Physical Factors on the Learning Motivation of Engineering Students

Furthermore, temperature in onsite setups exhibited the strongest relationship with learning motivation (β = 0.462, p = 0.001), demonstrating a highly significant impact. This suggests that maintaining an optimal temperature in physical classrooms is crucial for improving student motivation in hybrid learning setups. Aydin & Göktaş (2023) identified temperature as the most influential physical factor affecting students, reducing motivation and distracting attention. However, Liu et al. (2021) found that temperature differences had minimal practical significance, with performance variations of less than 2% across different thermal conditions. These contrasting perspectives indicate that while extreme temperature fluctuations may hinder motivation and focus, slight variations may not necessarily impact academic performance. Lastly, results showed that air quality has no significant impact on learning motivation. In an online setup, the path coefficient was 0.016 ($p = 0.865$), while in an onsite setup, it was -0.086 ($p = 0.341$), indicating weak and non-significant effects. This suggests that air quality does not influence comprehension, participation, productivity, comfort, or concentration

Table 3. Impact of Macro Ergonomic Factors on the Learning Motivation of Engineering Students in a Hybrid Learning Setup - Full Model

Paths	Estimate	Standard Error	z-value	p-value
Learning Motivation				
Teacher-Student Interactive Method	0.101	0.203	0.496	0.620
Student-centered Method	0.570	0.098	5.839	< 0.001*
Study Management	0.152	0.058	2.614	0.009*

**Denotes significance at a 5% significance level*

Table 3 SEM results indicate that teacher-student interactive methods do not significantly impact learning motivation, suggesting their effectiveness may depend on other factors not captured in this model. However, student-centered methods and effective use of learning management systems play a crucial role in enhancing motivation in a hybrid learning environment. The results of the study support the findings of Kerimbayev et al. (2023) where they highlighted that a student-centered approach with modern technologies enhances motivation, flexibility, and digital literacy, contributing to improved learning outcomes. Additionally, Wang (2023) reinforced this by emphasizing that student-centered learning fosters intrinsic motivation, personalized experiences, and active participation.

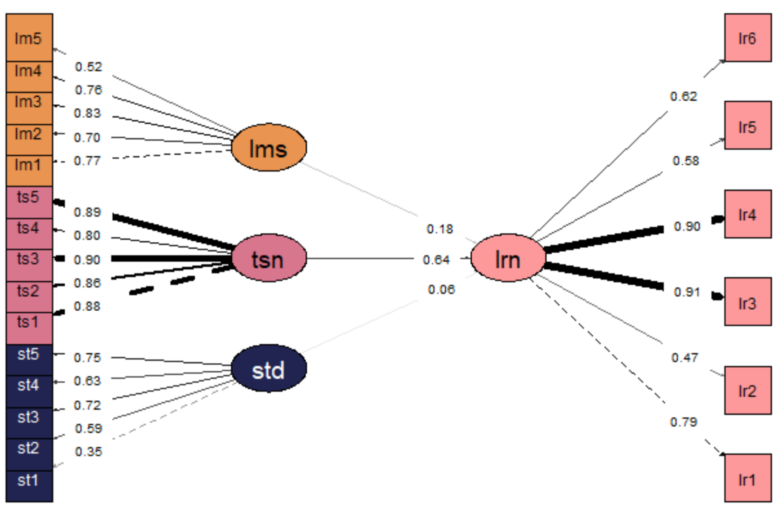

Figure 4. Path Diagram with Standardized Coefficients for the Model of the Macro Ergonomic Factors on the Learning Motivation of Engineering Students

Table 4. Impact of Learning Motivation on the Academic Performance of Engineering Students in a Hybrid Learning Setup - Full Model

Paths	Estimate	Standard Error	z-value	p-value
Academic Performance				

Learning Motivation	0.066	0.034	-1.960	0.050*

**Denotes significance at a 5% significance level*

Table 4 results show a marginally significant relationship between learning motivation and academic performance (GWA). The regression coefficient (0.066, p = 0.050) suggests that increased motivation slightly improves academic performance, though the evidence is not strong enough for definitive conclusions. These results align with prior research that highlights the relationship between motivation and academic achievement. Liu et al. (2022) supported this finding that intrinsic motivation consistently correlates with academic success, while extrinsic motivation becomes more influential as students mature. Muhammad et al. (2021) also confirmed a significant positive relationship between motivation and academic performance, emphasizing the importance of fostering motivation to enhance student achievement. Similarly, Gumasing & Castro (2023) revealed that learning motivation affects students' academic attention in an online learning setup, further supporting its role in overall academic success.

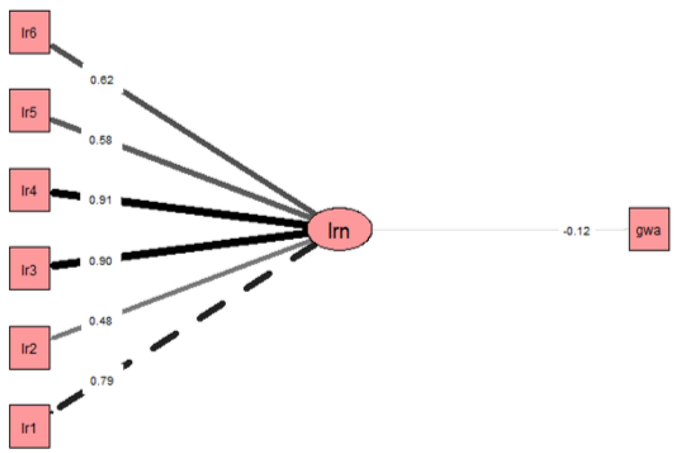

Figure 5. Path Diagram with Standardized Coefficients for the Model of the of Learning Motivation on the Academic Performance of Engineering Students

5.2 Reduced PLS-SEM Model

The reduced Partial Least Square-Structural Equation Model (PLS-SEM) were derived by removing insignificant latent variables from the initial comprehensive model to improve clarity and focus on the significant factors influencing learning motivation. Accepted latent variables were attendance, temperature onsite, illumination onsite, noise onsite, use of learning management system, and student-centered teaching method.

5.3 Proposed Improvements

Future research can improve this study by increasing the number of respondents and including participants from universities nationwide. Expanding the sample size, especially in the National Capital Region (NCR), will provide a more representative analysis and account for differences across institutions and locations. Additionally, including students from different academic fields beyond engineering can help identify discipline-specific motivation patterns, making the findings more applicable to a wider student population. Further studies should also examine other behavioral factors that influence learning motivation. Investigating ergonomic aspects such as workstation arrangement, seating comfort, and overall physical environment can provide deeper insights into their impact on student motivation and productivity. Moreover, analyzing gender and age as moderating factors can help determine how different groups respond to various learning conditions. Lastly, using a Likert scale instead of numerical grades to assess academic performance could offer a more subjective and detailed view of students' learning progress and satisfaction, capturing insights that traditional grading methods might miss.

6.Validation

The table below shows the convergent validity of each construct in the study. A good and acceptable reliability (Cronbach's alpha) indicates that there is a (1) large number of test items or questions, (2) homogeneity of items, and (3) well-interrelated items (Ekulo and Quianoo, 2019). Ekulo and Quainoo (2019) emphasized that an acceptable reliability lies between 0.5 and 0.8, whereas a good reliability is greater than 0.8. Aderinan (2019) further suggests that a Cronbach's alpha of 0.70 is acceptable for exploratory research, while 0.80 and 0.90 are acceptable for basic research. In SEM, composite reliability is often done to measure the internal consistency of reliability (Hair et al., 2016). Cheung et al. (2023) argued that a composite reliability greater than 0.7 or 0.8 indicates a more consistent construct reliability. Fornell and Larcker (1981) suggest that the average variance extracted (AVE) should be greater than 0.5. Therefore, all the criteria were met.

Table 5. Construct Reliability and Validity

Factor	Cronbach's Alpha	Composite Reliability	AVE
Student Workload	0.805	0.868	0.575
Attendance	0.826	0.878	0.591
Noise Online	0.803	0.864	0.562
Noise Onsite	0.903	0.928	0.722
Illumination Online	0.842	0.889	0.619
Illumination Onsite	0.903	0.929	0.724
Temperature Online	0.943	0.956	0.814
Temperature Onsite	0.950	0.613	0.285
Air Quality Online	0.920	0.944	0.772
Air Quality Onsite	0.950	0.962	0.835
Student-centered method	0.759	0.839	0.513
Teacher-student interactive method	0.759	0.839	0.513
Study management (use of LMS)	0.759	0.839	0.513
Learning Motivation	0.869	0.903	0.610

Fornell and Larcker propose a conventional criterion that compares the squared AVE (Average Variance Extracted) of each latent variable with the shared variances of all other latent variables in the structural model evaluated using reflective indicators.

Table 6. Discriminant Validity (Fornell-Larcker Criterion)

	ATT	WRK	LM	AQNS	AQNL	TMPNS	TMPNL	ILLMNS	ILLMNL	NSN	NSL	LMS	TSN	STD
Attendance	**0.769**													
Student Workload	0.382	**0.759**												
Learning Motivation	0.563	0.374	**0.781**											
Air Quality Onsite	0.468	0.263	0.565	**0.914**										
Air Quality Online	0.415	0.31	0.519	0.785	**0.878**									
Temperature Onsite	0.491	0.248	0.735	0.709	0.583	**0.914**								
Temperature Online	0.465	0.273	0.641	0.589	0.64	0.761	**0.902**							
Illumination Onsite	0.581	0.414	0.644	0.635	0.548	0.65	0.556	**0.851**						
Illumination Online	0.522	0.454	0.534	0.556	0.615	0.515	0.498	0.71	**0.787**					
Noise Onsite	0.486	0.294	0.557	0.474	0.402	0.559	0.464	0.574	0.529	**0.85**				
Noise Online	0.437	0.33	0.429	0.396	0.464	0.447	0.527	0.502	0.515	0.577	**0.75**			
Study Management (Use of Learning Management System)	0.349	0.182	0.541	0.431	0.391	0.48	0.469	0.433	0.393	0.346	0.344	**0.783**		
Teacher-student Interactive Method	0.532	0.258	0.718	0.608	0.496	0.752	0.602	0.621	0.502	0.583	0.432	0.507	**0.893**	
Student-Centered Method	0.435	0.318	0.6	0.585	0.586	0.624	0.595	0.541	0.557	0.497	0.414	0.54	0.701	**0.716**

Abbreviations: *Attendance (Att), Student Workload (WRK), Learning Motivation (LM), Air Quality Onsite (AQNS), Air Quality Online (AQNL), Temperature Onsite (TMPNS), Temperature Online (TMPNL), Illumination Onsite (ILLMNS), Illumination Online (ILLMNL), Noise Onsite (NSN), Noise Online (NSL), Learning Management System (LMS), Teacher-student Interactive Method (TSN), Student-Centered Method (STD)*

Table 6 displayed the fit indices such as the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Standardized Root Mean Square Residual (SRMR) of the model. With this, the model provided an adequate approximation of the data and considered to be a good fit as all values fall above the acceptable threshold based on cited literature.

Table 7. Global Fit Measures for the Model of the All Factors on the Learning Motivation and Learning Motivation on the Academic Performance of Engineering Students

Fit Measures		Estimate	Adequate Fit Index
Comparative Fit Index (CFI)	Behavioral Factors	0.918	CFI ≥ 0.90 (Hooper et al., 2008; Asparouhov & Muthén, 2018)
	Physical Factors	0.916	
	Macro Ergonomic Factors	0.913	
	Learning Motivation	0.935	
Tucker-Lewis Index (TLI)	Behavioral Factors	0.903	TLI ≥ 0.90 (Hooper et al., 2008; Asparouhov & Muthén, 2018)
	Physical Factors	0.909	
	Macro Ergonomic Factors	0.901	
	Learning Motivation	0.902	
Standardized Root Mean Square Residual (SRMR)	Behavioral Factors	0.076	SRMR ≤ 0.08 (Kim et al., 2016)
	Physical Factors	0.046	
	Macro Ergonomic Factors	0.070	
	Learning Motivation	0.068	

Conclusion

The study's objectives to identify and examine the influence of behavioral, physical, and macro-ergonomic factors on the learning motivation of engineering students in a hybrid learning setup were effectively observed. The study concludes that attendance, student-centered teaching methods, and effective study management using a Learning Management System (LMS) have a significant and positive impact on learning motivation. This indicates that increased class attendance, engagement in student-centered learning, and effective use of platforms like Canvas correlate with increased motivation for learning. While learning motivation was found to have a marginally significant impact on academic performance, further research with a larger sample size may be needed to fully understand this relationship. However, the study also found that certain factors, such as noise, temperature, illumination, air quality, student workload, and teacher-student interactive methods, did not have a consistent or significant impact on engineering students' learning motivation in the hybrid learning environment. This inconsistency originates from the hybrid learning approach, which blends online and on-site learning methods, each with its own set of problems and qualities. This research contributes to unique insights by emphasizing actionable areas for improvement in the hybrid learning environment. Recommendations from this study can be used to develop effective strategies, including flexible attendance rules, student-centered teaching strategies, and improved LMS integration. This study presents a useful framework for educators, institutions, and students to build an engaging, supportive, and productive hybrid learning environment.

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