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Examining the Effects of Project-Based Learning on STEM Students' Non-Cognitive Variables: An RPP and MDS Approach

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Abstract: *This study investigates the effects of project-based learning (PBL) courses on higher-education STEM students by examining changes in students' non-cognitive variables. The variables examined include learning satisfaction, grit, growth mindset, fixed mindset, and self-efficacy. To reduce response shift bias and missing data while providing a more accurate baseline, this study adopts a retrospective pretest–posttest (RPP) design to assess changes in these variables from the beginning to the end of the semester following students' participation in PBL courses. To explore the latent structures underlying these changes, the difference scores between the retrospective pretest and posttest are used as dependent variables. Multidimensional scaling (MDS) is employed to conduct variable reduction and structural analysis. The participants consist of students from four departments at a university in Taiwan, representing the four STEM domains: science, technology, engineering, and mathematics. The MDS results reveal that the latent structure of the non-cognitive variables can be represented by three dimensions. Dimension 1 reflects overall improvements across all non-cognitive variables. Dimension 2 represents improvements in all non-cognitive variables except fixed mindset. Dimension 3 indicates improvements in learning satisfaction accompanied by a decrease in growth mindset. These findings provide new insights into the latent structure of non-cognitive development among STEM students engaged in project-based learning. Furthermore, the methodological approach combining the RPP design with multidimensional scaling offers a novel analytical framework for examining changes in non-cognitive variables in educational research.*

Keywords: multidimensional scaling, project-based learning, retrospective pretest-posttest, STEM

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1. Introduction

STEM education, which comprises the education of science, technology, engineering, and mathematics, represents an interdisciplinary field cluster that integrates scientific inquiry, technological tools, engineering design, and quantitative reasoning to address authentic and complex problems (Reinholz, White, & Andrews, 2021). STEM education increasingly emphasizes interdisciplinary learning, real-world problem solving, and innovation. Universities integrate project-based learning, computational thinking, and digital technologies to develop students' transferable skills and prepare a workforce capable of adapting to rapid technological change. In higher education, STEM functions not only as a collection of academic majors but also as a talent-development engine that cultivates transferable competencies, including modeling, computational thinking, evidence-based decision making, and innovation-oriented problem solving. These competencies are increasingly associated with economic productivity and the growing demand for STEM-capable professionals, particularly those holding bachelor's degrees or higher (Mezinska, Abolina, & Lubkina, 2024).

The implementation of STEM education in universities is essential for preparing students to address complex real-world problems through interdisciplinary knowledge and innovation. It cultivates critical thinking, technological competence, and problem-solving abilities, while fostering a workforce capable of supporting economic development and adapting to rapid technological change (Fakayode, Yakubu, Adeyeye, Pollard, & Mohammed, 2014). At the institutional level, strengthening undergraduate STEM education enhances teaching effectiveness and equity by promoting student-centered and evidence-informed instructional practices and by reducing barriers that contribute to uneven participation and outcomes across student groups. At the classroom level, STEM learning experiences that emphasize design processes and real-world challenges foster transversal competences, such as collaboration, creativity, and communication, which support innovation across disciplines and industries. Therefore, STEM education in higher education plays a critical role not only in preparing specialized professionals but also in developing a broadly STEM-literate citizenry and workforce capable of adapting to rapid technological change.

Project-based learning (PBL) emphasizes learning through engaging in authentic projects and solving real-world problems. It promotes active inquiry, collaboration, and critical thinking, enabling students to construct knowledge while developing problem-solving skills and meaningful connections between theory and practice. PBL has emerged as a powerful pedagogical approach that situates student learning in sustained, real-world problem solving, fostering deep engagement, collaboration, and the development of 21st-century competencies beyond rote memorization. In the context of STEM education, PBL serves as a cornerstone for integrating disciplinary knowledge and practices, enabling learners to apply science, technology, engineering, and mathematics concepts in authentic interdisciplinary tasks that mirror the complexity of real societal problems. Recent scholarship frames PBL as a catalyst for integrated STEM learning, highlighting its role in promoting interdisciplinary understanding, equity, and innovative thinking through sustained project design and implementation (Lee & Lee, 2025). Meta-analytic evidence further confirms that PBL significantly enhances academic achievement, higher-order thinking, and affective attitudes compared to traditional instruction, particularly within engineering and technology contexts (Zhang & Ma, 2023). Moreover, STEM-PBL approaches have been shown to improve students' creativity and problem-solving skills, demonstrating statistically meaningful effects on learners' ability to generate and apply novel solutions (Kwon, 2025). Collectively, these findings underscore that PBL not only deepens STEM content mastery but also cultivates essential cognitive and collaborative competencies critical for success in a rapidly evolving, innovation-driven society. PBL in STEM education has shown to significantly enhance students' non-cognitive outcomes. These non-cognitive outcomes means to improve learning satisfaction, grit, growth mindset, and self-efficacy and reduce fixed mindset (Lin, & Chuang, 2017). Related literatures suggest that PBL in STEM education not only strengthens content learning but also cultivates essential motivational and psychological characteristics that support sustained engagement and adaptive learning behaviors (Liu & Lian, 2026).

The retrospective pretest–posttest (RPP) design measures perceived changes by asking participants to evaluate their prior and current status at the same time. The RPP is a self-report change design in which participants rate their current status at posttest and then retrospectively rate their pre-intervention status using the same frame of reference. Methodologically, RPP reduces response shift bias and missing data, providing a more accurate baseline and improving the validity of evaluating changes after educational interventions. This approach is widely used to reduce response-shift bias, —a recalibration of internal standards that can distort traditional pretest–posttest comparisons—while remaining practical for program evaluation and educational interventions (Hill, 2020; Kowalski, 2023). Recent empirical work also shows that RPP and traditional designs can yield meaningfully different estimates of growth, underscoring the importance of design choice when interpreting change (Fan et al., 2025). Multidimensional scaling (MDS) is an exploratory ordination technique that transforms a matrix of (dis)similarities into a low-dimensional map, where proximity represents similarity in patterns. When applied to RPP difference scores, MDS offers a methodological innovation: instead of testing each outcome separately, researchers can build a dissimilarity structure among change variables or individuals' change profiles. It can also reveal latent geometric patterns that summarize how multiple outcomes co-move over time. This provides an interpretable for theory-building and variables reduction, aligning with modern psychometric uses of MDS for extracting latent features from complex educational data (Tang et al., 2020).

In STEM education, non-cognitive variables such as learning satisfaction, grit, growth mindset, fixed mindset, and self-efficacy play a crucial role in students' learning processes. These factors influence students' motivation, persistence, and engagement, thereby shaping their ability to overcome challenges and sustain long-term success in STEM learning Based on the above considerations, this study investigates the effects of PBL courses on university STEM students by applying MDS to analyze changes in students' non-cognitive variables. These non-cognitive variables include learning satisfaction, grit, growth mindset, fixed mindset, and self-efficacy.

2. Literature Review

STEM Education and Project-based Learning

The development of competencies among STEM students in higher education is essential for addressing complex technological and societal challenges. Universities cultivate analytical thinking, problem-solving, and innovation abilities, enabling students to apply interdisciplinary knowledge and adapt to rapidly evolving scientific and technological environments (Hall, & Miro, 2016; Martín-Páez, Aguilera, Perales-Palacios, & Vílchez-González, 2019). In higher education, STEM education has become a strategic priority because universities are expected not only to build disciplinary knowledge, but also to cultivate transferable competencies (e.g., problem solving, teamwork, design thinking) that match rapidly shifting technological and labor-market demands. Recent scholarship emphasizes that effective integrated STEM is characterized by authentic, real-world problem contexts, inquiry/design practices, and collaborative work—features that align well with university-level curricula that aim to prepare graduates for complex societal challenges (Portillo-Blanco et al., 2024). In engineering and other STEM majors, the "future skills" agenda further highlights the need for interdisciplinary learning environments that intentionally foster creativity, communication, and systems thinking for Industry 4.0 contexts (Azofeifa et al., 2024). Likewise, innovation-oriented higher education STEM increasingly stresses transversal competences as foundations for design-driven innovation and student readiness to generate solutions beyond routine technical tasks (Mezinska et al., 2024). Complementing these trend lines, evidence from higher education STEM initiatives (e.g., service learning and community-engaged STEM) suggests a growing shift toward experiential, impact-focused learning models that connect academic STEM knowledge with social needs and professional identity formation (Mahmud & Ismail, 2024).

PBL is widely defined as a learner-centered pedagogy in which students investigate an authentic driving question and produce concrete artifacts through iterative inquiry, collaboration, and reflection. This structure is highly compatible with integrated STEM because it naturally integrates scientific reasoning, technological tools, engineering design cycles, and mathematical modeling within a single meaningful task. Empirical work in i-STEM PBL reports that implementation is feasible when instructors scaffold collaboration, provide design constraints, and support students' sense-making across disciplines (Chang & Chen, 2022). At the broader evidence level, meta-analytic findings indicate that PBL yields positive learning effects across contexts, supporting its value as a high-impact practice rather than a niche method (Zhang & Ma, 2023). Within STEM-specific research, PBL is also framed as a catalyst for integrated STEM because it operationalizes "integration" through shared design goals and tangible products that make cross-disciplinary connections visible to learners (Lee & Lee, 2025). Moreover, STEM-PBL meta-analytic evidence suggests robust benefits for outcomes such as creativity, reinforcing its role in developing higher-order competencies that higher education STEM increasingly prioritizes (Kwon & Lee, 2025).

Retrospective Pretest–Posttest Measurement and Multidimensional Scaling

The RPP design plays an important role in educational methodology by assessing participants' perceived changes after an intervention. By asking respondents to evaluate both prior and current states at the same time, it reduces response shift bias and missing data, thereby providing a more accurate baseline for measuring learning outcomes (Little, Chang, Gorrall, Waggenspack, Fukuda, Allen, & Noam, 2020). RPP design originated in program evaluation research as a methodological response to limitations inherent in traditional pretest–posttest designs, particularly response shift bias. Howard, Ralph, Gulanick, Maxwell, Nance, and Gerber (1979) first conceptualized the retrospective approach, arguing that participants' internal standards, frames of reference, and understanding of constructs often change following an intervention, rendering initial pretest scores invalid. By asking participants at the posttest stage to rate both their current status and their perceived status prior to the intervention, RPP allows respondents to make judgments using a common cognitive framework. Empirical studies have demonstrated that RPP reduces response shift bias, minimizes missing data, and enhances the validity of self-reported change, especially in affective and non-cognitive domains such as attitudes, self-efficacy, and motivation (Allen & Nimon, 2007; Hill & Betz, 2005). Compared with traditional pretest–posttest designs, RPP is more efficient, less intrusive, and better suited for educational contexts where learners' conceptual understanding evolves substantially during instruction. Moreover, RPP has been shown to yield effect estimates comparable to or more conservative than traditional designs, suggesting that it provides a robust alternative for evaluating instructional interventions and professional development programs (Pratt, McGuigan, & Katzev, 2000).

MDS plays an important role in quantitative research and methodology by revealing the underlying structure of complex data. It represents relationships among variables or observations in a low-dimensional space, allowing researchers to visualize similarities and patterns. This approach supports variable reduction and provides deeper insights into latent structures in educational and social science research (Saeed, Nam, Haq, & Muhammad Saqib, 2018). MDS is a set of data-reduction and visualization techniques designed to represent the latent structure of proximity or dissimilarity data in a low-dimensional geometric space. Originating from psychometrics and mathematical psychology, MDS enables researchers to explore underlying relationships among variables when theoretical structures are uncertain or multidimensional (Hout, Papesh, & Goldinger, 2013). Modern applications of MDS emphasize its exploratory power in revealing latent dimensions, construct configurations, and relational patterns that may not be evident through traditional factor-analytic approaches. In the context of RPP measurement design, applying MDS to pretest–posttest difference scores represent a methodological innovation. Difference scores, when carefully interpreted, capture meaningful change trajectories rather than static levels (Edwards, 2001). By treating RPP difference scores as proximity inputs, MDS enables researchers to examine how multiple non-cognitive outcomes co-vary and cluster within a reduced dimensional space, thereby revealing latent change structures across constructs. This approach extends the analytical utility of RPP beyond mean comparisons by integrating change-score modeling with spatial representation, offering a novel framework for investigating the multidimensional effects of educational interventions.

3. Methodologies

To address the purposes of this study, this section outlines the overall research design, the participants involved in the PBL courses, and the operational definitions of the key variables examined in the study. In addition, it explains how the research framework is implemented to investigate changes in students' non-cognitive variables and to ensure methodological clarity and consistency in the data collection and analysis procedures.

Research Design

The research framework and procedures of this study are presented in Figure 1. The participants are undergraduate students who enroll in required PBL courses over one academic semester, from September 2024 to January 2025. At the end of the semester, a RPP measurement is administered to assess students' non-cognitive latent traits, including learning satisfaction, grit, fixed mindset, growth mindset, and self-efficacy. The RPP instrument in this study adopts a five-point Likert scale to capture students' perceived levels before and after participating in the PBL courses. Based on the pretest–posttest difference scores derived from the RPP measurements, MDS analysis is conducted to examine the relationships among the non-cognitive variables and to explore their underlying structural patterns. This analytical approach enables the study to identify latent dimensions and provide a clearer interpretation of the changes in students' non-cognitive development within the context of PBL learning in higher education.

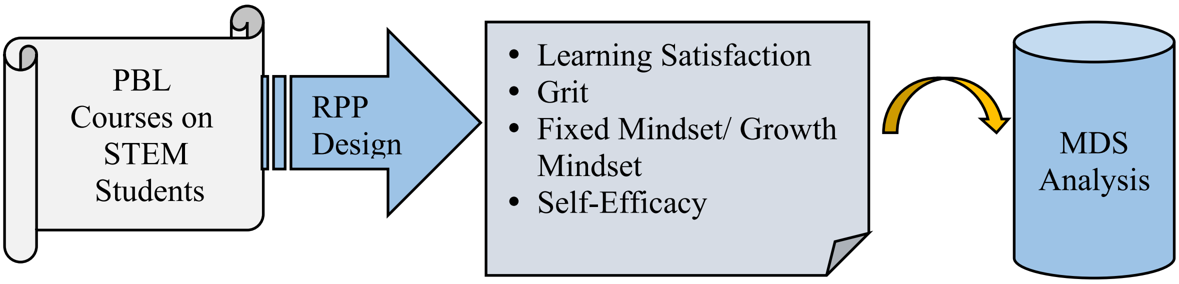

Figure 1: Research Framework and Procedure

Participants of PBL Courses

The sample of this study consists of 173 undergraduate students enrolled in four academic fields: science education and application, digital content and technology, computer science, and mathematics and mathematics education. These students represent the major domains of STEM disciplines and participate in PBL courses designed to promote interdisciplinary learning and problem-solving abilities. The inclusion of students from diverse STEM-related programs provides a broader perspective for examining changes in their non-cognitive variables within higher education contexts.

Definition of Non-Cognitive Variables
The definitions of the non-cognitive variables examined in this study are described as follows. Learning satisfaction is an important construct in educational psychology and refers to students' feelings and attitudes toward learning activities, reflecting the extent to which their needs, expectations, and learning experiences are fulfilled during the learning process (Topala & Tomozii, 2014). It is often regarded as an indicator of students' perceived quality of the learning environment and their overall evaluation of instructional effectiveness. In the context of this study, learning satisfaction refers to students' perceived level of satisfaction with course instruction, learning support, and environmental resources throughout the implementation of PBL. This construct captures how students evaluate the instructional design, teacher guidance, peer interaction, and learning resources provided during the PBL process. A higher level of learning satisfaction suggests that students perceive the learning activities as meaningful, supportive, and conducive to their engagement and academic development.

Grit is an important construct in positive psychology and is generally conceptualized as consisting of two dimensions: consistency of interest and perseverance of effort. It refers to the tendency of individuals to sustain long-term interest and persist in their efforts when pursuing challenging goals, even in the face of difficulties or setbacks (Duckworth, Peterson, Matthews, & Kelly, 2007). In educational contexts, grit has been associated with students' persistence, sustained engagement, and long-term commitment to learning tasks. In this study, grit is defined as students' sustained interest in and persistent effort toward PBL tasks throughout the research-oriented learning process. It reflects the extent to which students remain committed to completing complex projects, overcoming learning challenges, and continuously investing effort in inquiry, collaboration, and problem-solving activities within the PBL learning environment.

Mindset is an important construct in positive psychology and refers to individuals' beliefs about the nature of their abilities and the possibility of improving those abilities through effort and learning. According to Dweck (2016), mindset can be broadly categorized into two types: growth mindset and fixed mindset. Individuals with a growth mindset believe that their abilities are malleable and can be developed through continuous learning, effort, and effective strategies. As a result, they are more willing to embrace challenges, persist in the face of difficulties, and view setbacks as opportunities for improvement. In contrast, individuals with a fixed mindset believe that their abilities are relatively stable and unlikely to change. This belief often leads them to avoid challenging tasks and to give up more easily when encountering obstacles or failures. In educational contexts, students' mindsets influence their motivation, persistence, and engagement in learning activities. In this study, growth mindset and fixed mindset refer to students' beliefs about their abilities and performance during the process of project-based learning (PBL). Specifically, growth mindset reflects students' belief that their competencies in conducting project-based research tasks can improve through effort and learning, whereas fixed mindset reflects the belief that such competencies are largely predetermined and difficult to change. These beliefs shape how students approach challenges and persist in completing complex PBL tasks.

Self-efficacy is a central construct in social cognitive psychology proposed by Albert Bandura and refers to individuals' beliefs about their capabilities to organize and execute the actions required to accomplish specific goals or perform particular learning tasks. It reflects the degree of confidence individuals have in their ability to manage challenges and achieve desired outcomes. Self-efficacy plays a crucial role in regulating motivation, effort, persistence, and performance in learning contexts. Individuals with higher self-efficacy are more likely to set challenging goals, exert sustained effort, and persist when facing difficulties, whereas those with lower self-efficacy are more likely to experience doubts about their abilities and demonstrate less effective performance (Schwarzer & Luszczynska, 2023). In educational settings, self-efficacy has been widely recognized as an important factor influencing students' engagement and academic achievement. In this study, self-efficacy is defined as students' beliefs in their capability to successfully engage in and complete project-based research tasks throughout the learning process. It reflects students' confidence in their ability to conduct inquiry, apply relevant knowledge and skills, collaborate with peers, and overcome challenges encountered during the implementation of PBL.

4. Analysis and Discussion

The following sections present an analysis of the statistical characteristics of the variables measured through the RPP design, as well as the model selection results obtained from MDS analysis. Descriptive statistics and related indicators are first examined to understand the distributional features and change patterns of the non-cognitive variables. Subsequently, the MDS results are reported to determine the appropriate dimensional structure that best represents the relationships among these variables. In addition, the latent traits represented by each dimension identified in the MDS model are further interpreted in order to clarify their underlying meanings and to provide a more comprehensive understanding of the structural patterns among the non-cognitive variables.

RPP Variables and Model Selection

In the RPP design used in this study, the difference score is calculated by subtracting the beginning-of-semester score from the end-of-semester score. This difference reflects the magnitude and direction of students' perceived changes in each non-cognitive variable after participating in the PBL courses. Table 1 summarizes the number of items for each variable, together with the mean and standard deviation of the corresponding difference scores. As shown in Table 1, the results indicate that fixed mindset is the only variable that demonstrates a decrease from the beginning to the end of the semester, whereas all other variables—including learning satisfaction, grit, growth mindset, and self-efficacy—show higher scores at the end of the semester. This pattern suggests that students tend to report improvements in most of the examined non-cognitive variables after participating in the PBL courses. In particular, the decrease in fixed mindset may imply that students become less inclined to perceive their abilities as fixed and more open to developing their competencies through learning and effort. Overall, these findings provide preliminary evidence that the PBL courses implemented in this study have positive influences on the development of STEM students' non-cognitive characteristics.

Table 1: Descriptions of Difference Score in RPP Measurement

Variables	Number of Items	Descriptions of Difference Score	
		Mean	Standard Deviation
Learning Satisfaction	6	3.1696	1.93728
Grit	8	3.2811	1.85880
Fixed Mindset	4	-1.3150	3.08817
Growth Mindset	4	2.7934	2.13352
Self-Efficacy	6	3.1175	1.86521

Table 2 presents the correlation coefficient matrix of the difference scores obtained from the RPP measurements. These correlation coefficients illustrate the relationships among the changes in the non-cognitive variables following students' participation in the PBL courses. The results indicate that learning satisfaction is significantly and positively correlated with grit, growth mindset, and self-efficacy, suggesting that students who report greater increases in learning satisfaction also tend to demonstrate stronger improvements in persistence, growth-oriented beliefs, and confidence in their learning capabilities. In contrast, learning satisfaction is not significantly correlated with fixed mindset, indicating that changes in students' satisfaction with the learning experience are not strongly associated with changes in their fixed beliefs about ability. These findings suggest that the most prominent effects of the PBL courses in STEM education within this study are reflected in the enhancement of students' learning satisfaction. Moreover, the positive associations between learning satisfaction and other adaptive non-cognitive variables imply that a supportive and engaging PBL learning environment may contribute to strengthening students' motivation, persistence, and self-beliefs during the learning process.

Table 2: Correlation Coefficients among RPP Variables

	Learning Satisfaction	Grit	Fixed Mindset	Growth Mindset	Self-Efficacy
Learning Satisfaction	-				
Grit	.806**	-	-		
Fixed Mindset	.018	.018	-		
Growth Mindset	.592**	.601**	.144	-	
Self-Efficacy	.726**	.835**	.097	.642**	-

***p<.01

Table 3 presents several model selection indices obtained from MDS analysis, comparing solutions with two to four dimensions. These indices are used to evaluate the goodness-of-fit and to determine the most appropriate dimensional structure for representing the relationships among the RPP difference-score variables. As shown in Table 3, when the number of dimensions is set to three, the values of Normalized Raw Stress, Kruskal's Stress, and Stress for Squared Distances all reach their lowest levels, indicating that the three-dimensional configuration provides the best fit to the observed data. Furthermore, when the dimensionality is three, both the Dispersion Accounted For (D.A.F.) and Tucker's Coefficient of Congruence attain their highest values, suggesting that the three-dimensional model captures a greater proportion of the variance in the dissimilarity matrix and achieves a higher level of structural consistency. Taken together, these model selection criteria indicate that the three-dimensional solution provides the most appropriate representation of the relationships among the non-cognitive variables derived from the RPP measurements. Therefore, the three-dimensional configuration is selected as the optimal MDS model for interpreting the latent structure of the variables examined in this study.

Table 3: Thematic Analysis on Types of Perceptions Indices of Dimension Selection

Indices	**Number of Dimensions**		
	2	**3**	**4**
Normalized Raw Stress	0.01036	0.00474	0.00486
Kruskal's Stress	0.10179	0.06885	0.06972
Stress for squared distances	0.02330	0.01292	0.01300
D.A.F. (Dispersion Accounted For)	0.98964	0.99526	0.99514
Tucker's Coefficient of Congruence	0.99481	0.99763	0.99757

Relationships of MDS and RPP Variables

Table 4 presents the distributional characteristics and the results of the normality tests for the three dimension scores derived from the MDS analysis. These statistics provide information about the central tendency, variability, and distributional patterns of the dimension scores across the sample. As shown in Table 4, the results of the normality tests indicate that none of the three dimension scores follows a normal distribution. This finding suggests that the distributions of the dimension scores exhibit deviations from normality, which may be reflected in skewness or other irregular distributional patterns. Such results imply that the latent dimensions derived from the MDS analysis capture heterogeneous patterns of change in students' non-cognitive variables. Therefore, when interpreting these dimension scores, it is important to consider their non-normal distributional characteristics and the diverse responses of students to the PBL learning experience.

Table 4: Distributions of Three Dimensions

Descriptions of Statistics	**Dimensions**		
	Dim_I	**Dim_II**	**Dim_III**
Standard Deviation	.502692	450605	.204532
Skewness Coefficient	-.688	-.175	-.938
Kurtosis Coefficient	1.763	-.928	9.439
Kolmogorov-Smirnov test	.088***	.117***	.156***

***$p<.001$

Figures 2 to 4 respectively present the distribution plots of the scores for Dimension I to Dimension III derived from the MDS analysis. These figures provide a visual representation of the distributional patterns of the three dimension scores across the sample, allowing for a clearer understanding of their dispersion and shape. As illustrated in the figures, the distributions of the scores for Dimension I, Dimension II, and Dimension III do not follow a normal distribution. The graphical patterns reveal that the dimension scores exhibit irregular distributional forms, indicating variability in the degree to which students experience changes in the examined non-cognitive variables. These non-normal distributions suggest that the effects of the PBL courses on students' non-cognitive development are not uniform across individuals, but rather reflect diverse patterns of responses among STEM students participating in the learning activities.

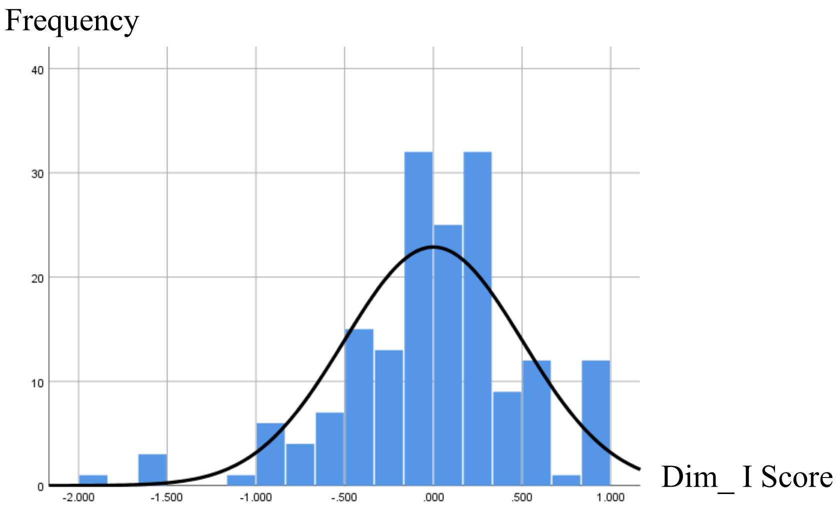

Figure 2: Distribution of Dimension I Score

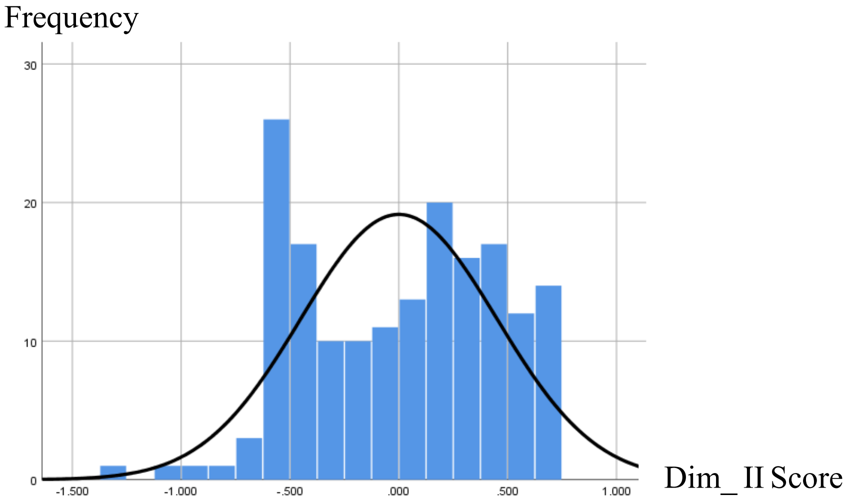

Figure 3: Distribution of Dimension II Score

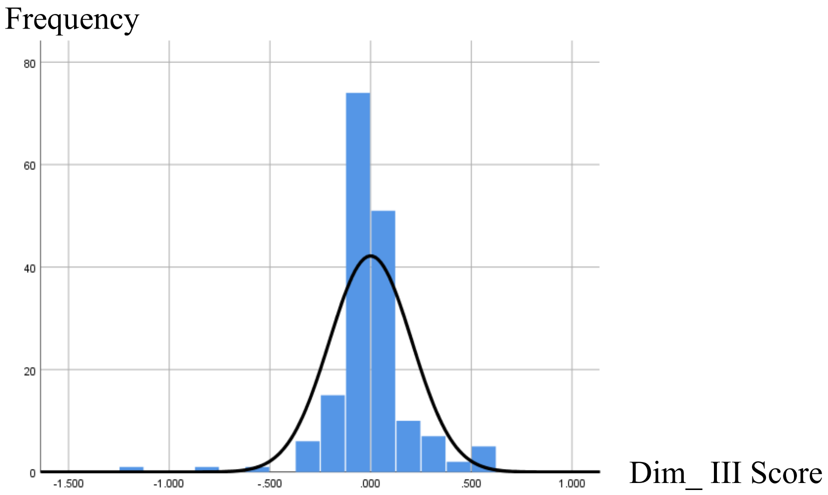

Figure 4: Distribution of Dimension III Score

Table 5 presents the heatmap of Pearson correlation coefficients between the RPP variables and the three dimension scores derived from the MDS analysis. The heatmap visually illustrates the strength and direction of the relationships between each non-cognitive variable and the latent dimensions identified in the MDS model, thereby facilitating the interpretation of the underlying meanings of these dimensions. The results show that Dimension I (Dim_I) demonstrates significant positive correlations with all RPP variables, including learning satisfaction, grit, fixed mindset, growth mindset, and self-efficacy. This pattern indicates that Dim_I reflects overall improvements in these non-cognitive variables from the beginning to the end of the semester under the RPP design. In other words, this dimension can be interpreted as representing a general positive development in students' non-cognitive characteristics during their participation in the PBL courses. Dimension II (Dim_II) is significantly correlated with all RPP variables and shows a significantly negative correlation with fixed mindset. This relationship suggests that Dim_II represents improvements in learning satisfaction, grit, growth mindset, and self-efficacy, accompanied by a decrease in fixed mindset over the semester. The interpretation of Dim_II therefore indicates that participation in PBL courses may promote more adaptive learning beliefs and motivational characteristics among STEM students. Dimension III (Dim_III) shows a significant positive correlation with learning satisfaction and a significantly negative correlation with growth mindset. This pattern suggests that Dim_III represents an increase in learning satisfaction accompanied by a decrease in growth mindset from the beginning to the end of the semester under the RPP design. The findings highlight that different latent dimensions capture distinct patterns of change in students' non-cognitive variables, reflecting the complex and multifaceted nature of students' responses to PBL learning experiences in STEM education.

Table 5: Heatmap of Correlation Coefficients between RPP Variables and Three Dimension Scores

RPP Variables	Three Dimension Scores		
	DIM_I	**DIM_II**	**DIM_III**
Learning Satisfaction	$.729^{**}$	$.487^{**}$	$.314^{**}$
Grit	$.748^{**}$	$.506^{**}$	.127
Fixed Mindset	$.516^{**}$	$-.831^{**}$	.043
Growth Mindset	$.828^{**}$	$.233^{**}$	$-.204^{**}$
Self-Efficacy	$.780^{**}$	$.412^{**}$	-.090

5. Conclusions

This study investigates the effects of PBL courses in STEM education by applying RPP measurement design to examine changes in students' non-cognitive variables before and after their participation in PBL courses. Specifically, the study focuses on key non-cognitive constructs, including learning satisfaction, grit, growth mindset, fixed mindset, and self-efficacy. By using the RPP design, the study is able to reduce response shift bias and capture students' perceived changes in these variables more accurately after completing the PBL learning experience. In addition, MDS is employed to reduce the dimensionality of the non-cognitive variables and to explore the latent structural relationships among them. Through the MDS analysis, the study identifies meaningful latent dimensions that reflect different patterns of change in students' non-cognitive development. The findings indicate that implementing PBL courses in university-level STEM education produces substantial positive effects on students' non-cognitive latent traits, particularly in enhancing learning satisfaction, persistence, and confidence in learning tasks. Furthermore, the integration of the RPP measurement approach with MDS analysis provides a novel methodological framework for examining changes in complex psychological and educational variables. This methodological combination not only strengthens the analytical interpretation of non-cognitive development in STEM learning environments but also offers valuable references for future research seeking to investigate the impacts of innovative instructional approaches in higher education.

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Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this study.

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