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The Impact of Hybrid Blended Learning on Learning Motivation among University Students: A PLS-SEM and IPMA Analysis

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ABSTRACT
The advancement of information technology has transformed higher education, leading to the adoption of blended learning—a combination of online and offline instruction. This study examines the impact of blended learning on learning motivation and identifies key motivational indicators for improvement. A quantitative survey was conducted with 115 fifth-semester students from the Informatics Engineering Study Program at Universitas Indraprasta PGRI, Jakarta. Data were collected using a validated and reliable five-point Likert-scale questionnaire and analyzed with Partial Least Squares Structural Equation Modeling (PLS-SEM) and Importance-Performance Map Analysis (IPMA) via SmartPLS software. Results indicate that blended learning has a positive and significant effect on students' learning motivation. IPMA findings indicate that "Flexibility of Time and Place" is the primary area for improvement, followed by Learning Interaction and Learning Effectiveness. At the same time, the Availability of Learning Facilities is a lower priority. Enhancing flexibility is expected to increase motivation substantially. These findings contribute to the development of student-centered learning models and offer practical guidance for educators and policymakers in designing more adaptive and engaging higher education learning environments.

Keywords: Hybrid, Blended Learning, Learning Motivation.

I. Introduction

The rapid advancement of information and communication technology has brought substantial transformation to the higher education landscape. One of the most prominent innovations emerging from this shift is the blended learning model, which strategically combines traditional face-to-face instruction with online learning components. This integration not only offers flexibility in terms of time and place but also fosters more dynamic and interactive engagement between lecturers and students. As a result, blended learning has been widely recognized for its potential to create adaptive and efficient

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learning environments that harness the strengths of both online and offline methods (Graham, 2006; Hrastinski, 2019). In addition to flexibility and accessibility, blended learning is valued for its ability to encourage active participation and self-directed learning. These attributes are especially relevant in the digital era, where higher education must adapt to meet the diverse needs and learning styles of students. By merging digital resources with in-person interaction, blended learning allows for more personalized learning experiences while maintaining opportunities for collaborative discussion and feedback.

Learning motivation plays a crucial role in determining the success of educational processes. Students with strong motivation tend to be more engaged, persistent, and capable of achieving better academic outcomes compared to those with lower motivation (Fitriyani et al., 2020; Umar et al., 2023). Motivation encompasses both internal drives, such as personal interest and goal orientation, as well as external factors, including recognition and academic rewards. Despite its importance, sustaining motivation can be challenging, particularly when learning environments are monotonous, lack interaction, or fail to address students' varying needs. Blended learning is expected to bridge this gap by creating a more engaging and interactive atmosphere. Previous research has demonstrated its ability to boost motivation through greater flexibility, increased learning autonomy, and the use of diverse content delivery methods (Putri & Nasution, 2023). For example, Siahaan and Pramana (2020) reported that blended learning significantly improved student motivation, academic performance, and instructional quality at Universitas Negeri Medan. Similarly, Isma et al. (2023) observed positive effects on motivation and learning outcomes at Universitas Negeri Makassar. Furthermore, Fitri et al. (2024) identified digital literacy as a mediating factor, indicating that students with strong digital skills are better positioned to benefit from blended learning. Santosa et al (2021) also confirmed that blended learning strategies outperform conventional approaches in enhancing motivation.

However, the extent to which blended learning enhances motivation varies depending on the context and quality of implementation. Prihastari and Yustinaningrum (2022) found only moderate levels of motivation among elementary education students in mathematics courses delivered through blended learning, suggesting the need for more tailored instructional strategies. In contrast, Siregar et al. (2023a) demonstrated that blended learning was an effective solution for maintaining motivation and engagement in nursing education during the COVID-19 pandemic. While many studies have explored the link between blended learning and motivation, most have focused on general outcomes without identifying which specific indicators of motivation, such as intrinsic drive, persistence, or interest in the subject, should be prioritized for improvement. This gap is critical because understanding which motivational aspects are both important and underperforming can help educators optimize instructional design. To address this gap, the present study not only examines the impact of blended learning on learning motivation but also identifies key motivational indicators that warrant targeted enhancement. By employing a quantitative approach supported by advanced analytical techniques such as Importance-Performance Map Analysis (IPMA), this research offers empirical insights and practical recommendations for developing more effective, student-centered learning interventions in the higher education context.

II. Literature Review and Hypothesis Development

2.1. Blended Learning

The rapid evolution of science and technology has transformed education, requiring educators not only to master pedagogical competence but also to adapt instructional strategies that integrate technological advancements (Chafshah et al., 2024; Harefa et al., 2024; Saripudin & Robbani, 2024). The COVID-19 pandemic accelerated this transformation, shifting traditional face-to-face instruction toward remote learning, characterized by the widespread use of digital devices and online platforms (Harahap & Napitupulu, 2023). Blended learning, defined as the strategic integration of face-to-face instruction with online learning, provides greater flexibility and opportunities for personalized learning experiences. Foundational works, such as Graham (2006) and Bonk & Graham (2012), position blended learning within the Constructivist Theory and the Community of Inquiry Framework, emphasizing learner-centered approaches that promote cognitive presence, social presence, and teaching presence. Compared to purely offline or purely online modes, blended learning leverages the strengths of both formats to create richer learning interactions and better accommodate diverse learning styles (Agustian & Salsabila, 2021; Schmidt, 2002). Empirical evidence demonstrates that blended learning can enhance academic outcomes, student engagement, and self-directed learning (Putri & Nasution, 2023). However, challenges remain. Limitations such as unequal access to technology, variations in digital literacy, and potential feelings of isolation among students must be addressed to fully realize its benefits (Norberg et al., 2011; Porter et al., 2016). In this study, blended learning is conceptualized through four indicators: (1) learning effectiveness, (2) time and place flexibility, (3) availability of learning facilities, and (4) learning interaction. These indicators serve as operational measures to evaluate how blended learning influences student motivation.

2.2. Learning Motivation

Motivation is a fundamental psychological construct that drives individuals to initiate, sustain, and achieve learning goals. Foundational educational psychology defines motivation as the internal force that directs behavior toward desired outcomes (Oemar, 2011; Sardiman, 2006; Yamin & Maisah, 2010). The Self-Determination Theory (Deci & Ryan, 1985) offers a contemporary framework, distinguishing between intrinsic motivation, driven by personal interest and satisfaction, and extrinsic motivation, driven by external rewards or pressures. While classic definitions emphasize motivation as a response to internal energy changes, affective arousal, and goal-directed behavior (Handiyani & Muhtar, 2022), contemporary studies highlight its dynamic interaction with learning environments. High motivation correlates with increased persistence, engagement, and adaptability in academic settings (Fitriyani et al., 2020; Umar et al., 2023). Conversely, motivation can decline in monotonous or non-interactive learning contexts, underscoring the need for stimulating instructional design. In practical terms, theories of learning motivation can guide educators in designing interventions that promote student autonomy, competence, and relatedness, key drivers of sustained engagement in blended learning environments. For example, aligning tasks with students' interests, providing timely feedback, and ensuring supportive peer interaction are proven strategies to enhance motivation in higher education (Schunk & DiBenedetto, 2020). For this study, learning motivation is operationalized using four measurable indicators: (1) enthusiasm for learning, (2) academic responsibility, (3) learning

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independence, and (4) academic goals. These indicators capture both the affective and behavioral dimensions of motivation, making them suitable for empirical analysis in blended learning contexts.

2.3. Hypothesis Development

The integration of technology in education, particularly through blended learning, aligns with contemporary pedagogical theories that emphasize learner-centered approaches and flexibility in instructional delivery (Bonk & Graham, 2012; Graham, 2006). Blended learning enables students to access diverse learning resources, interact with instructors and peers in both synchronous and asynchronous formats, and manage their learning pace more autonomously (Hrastinski, 2019). These characteristics are theoretically linked to increased learning motivation, as they address the key psychological needs of autonomy, competence, and relatedness, outlined in Self-Determination Theory (Deci & Ryan, 1985). Empirical studies reinforce this theoretical linkage. Putri and Nasution (2023) demonstrated that blended learning enhances active participation and learning autonomy, which are strong predictors of motivation. Siahaan and Pramana (2020) found improvements in motivation, learning outcomes, and instructional quality following the implementation of blended learning strategies. Similarly, Isma et al. (2023) reported that blended learning has a positive influence on motivation and learning outcomes in higher education contexts. Moreover, Serrano et al. (2019) revealed that digital literacy strengthens the impact of blended learning on motivation, suggesting that technology-enhanced learning environments can be particularly effective for digitally competent students.

However, literature also acknowledges variability in results depending on the subject area, instructional design, and student readiness. For example, Prihastari and Yustinaningrum (2022) observed only moderate motivational levels among elementary education students in mathematics through blended learning, indicating that its benefits are not universally guaranteed. These mixed findings underscore the importance of identifying specific motivational indicators that are most influenced by blended learning, enabling the design of targeted interventions to optimize student engagement. Drawing on theoretical and empirical evidence, this study posits that blended learning has a significant positive impact on the motivation to learn among students in higher education. Furthermore, by employing Importance-Performance Map Analysis (IPMA), the study aims to determine which motivational indicators—such as enthusiasm for learning, academic responsibility, learning independence, and academic goals—should be prioritized for improvement.

III. Research Method

3.1. Research Design

This study employed a quantitative approach, utilizing a survey method, to examine the impact of blended learning on students' learning motivation. This design was selected for its ability to objectively measure relationships between variables using numerical data collected through a structured questionnaire. The methodological framework builds upon previous blended learning studies. However, it distinguishes itself by integrating Importance-Performance Map Analysis (IPMA) to identify specific motivational indicators for improvement —an approach rarely applied in similar contexts.

3.2. Population and Sample

The population comprised all fifth-semester students enrolled in the Informatics Engineering Study Program at Universitas Indraprasta PGRI who had experienced blended learning, totaling 160 individuals. The sample size was calculated using the Slovin formula with a 5% margin of error, resulting in 115 respondents. A proportional random sampling technique was implemented by first grouping the population according to class sections, then randomly selecting respondents from each group in proportion to its size, ensuring balanced representation. Following Hair et al (2021), this number falls within the range considered a medium-sized sample for PLS-SEM analysis.

3.3. Ethical Considerations

All participants were provided with an informed consent form outlining the research purpose, procedures, and their rights as respondents. Participation was voluntary, and data confidentiality was ensured by anonymizing all responses and restricting access to the dataset solely for research purposes.

3.4. Data Collection Instrument

Data were collected using a closed-ended questionnaire based on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The instrument measured two variables:

a. Blended Learning (independent variable), measured using four indicators: learning effectiveness, time and place flexibility, availability of learning facilities, and learning interaction.
b. Learning Motivation (dependent variable), measured using four indicators: enthusiasm for learning, academic responsibility, learning independence, and academic goals.

These indicators were adapted from established theories and prior research to ensure theoretical validity and relevance.

3.5. Pilot Testing

Prior to full deployment, the questionnaire was pilot-tested with 30 respondents who had similar characteristics to the target population. Validity was assessed using Pearson's product-moment correlation, with all items exceeding the threshold value of 0.30, thereby confirming construct validity. Reliability was evaluated using Cronbach's Alpha, with all constructs achieving coefficients above 0.70, indicating high internal consistency.

3.6. Data Analysis Technique

Data analysis was conducted in two stages:

a. Descriptive Statistics – Measures such as mean, standard deviation, and frequency distributions were calculated to provide a general overview of the data.

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b. Inferential Analysis – Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied using SmartPLS 3. PLS-SEM is particularly suitable for analyzing complex models with latent variables, accommodating medium-sized samples, and handling data that do not meet normality assumptions. The analysis generated path coefficients, R^2 values, and significance levels (p-values) to test the hypothesized relationships.

Additionally, an Importance-Performance Map Analysis (IPMA) was conducted to identify blended learning indicators that are both critical to learning motivation and currently underperforming. This method provides practical guidance for prioritizing improvements in the implementation of blended learning.

IV. Results and Discussion

4.1. Descriptive Statistics

Descriptive analysis was conducted to obtain a general overview of students' perceptions regarding the blended learning model and their level of learning motivation.

Table 1. Descriptive Statistics of Blended Learning and Learning Motivation Variables

Criteria	Blended Learning	Learning Motivation
Mean	76.20	75.80
Median	75.00	76.00
Mode	70	76
Standard Deviation	9.505	11.497
Variance	90.354	132.179
Skewness	0.116	-0.015
Standard Error of Skewness	0.226	0.226
Kurtosis	-0.241	0.093
Standard Error of Kurtosis	0.447	0.447
Range	43	58

Based on the responses of 115 students, the blended learning variable recorded a mean score of 76,20, a median of 75,00, and a mode of 70, indicating generally positive perceptions of its implementation. The standard deviation (9,505) and variance (90,354) suggest moderate data dispersion. Skewness (0,116) and kurtosis (-0,241) indicate a symmetrical distribution that is slightly platykurtic, yet still within the acceptable range for normality. For the learning motivation variable, the mean score was 75,80, with a median of 76,00 and a mode of 76. These close central tendency values indicate a normal distribution. The standard deviation (11,497) and variance (132,179) reflect slightly greater variability compared to the blended learning variable. Skewness (-0,015) and kurtosis (0,093) confirm a symmetrical and near-normal distribution. Both variables meet the assumptions necessary for further analysis using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Importance-Performance Map Analysis (IPMA), ensuring the reliability of subsequent findings and their interpretation within the study's theoretical framework.

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4.2. Reflective Measurement Model

The measurement of the reflective model refers to the research constellation model below:

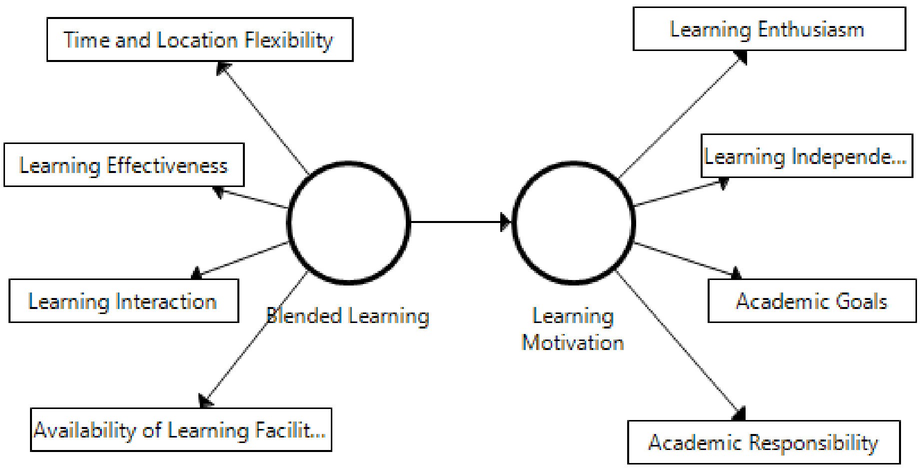

Figure 1. Research Constellation Model

From the reflective model measurements, several criteria were produced as follows:

Table 2. Outer Loading Values of Research Variable Indicators

Indicator	Blended Learning	Learning Motivation
Learning Enthusiasm		0.877
Learning Effectiveness	0.881	
Time and Location Flexibility	0.880	
Learning Interaction	0.893	
Learning Independence		0.907
Availability of Learning Tools	0.860	
Academic Responsibility		0.836
Academic Goals		0.876

The reflective measurement model was assessed to ensure that the indicators accurately represent their respective latent constructs. This was done by examining the outer loading values of each indicator. In reflective models, an indicator is considered valid if its loading value exceeds 0,70, indicating that it effectively reflects the intended construct (Hair Jr et al., 2021). As shown in Table 2, all indicators in this study meet this criterion. For the blended learning construct, the indicators — learning effectiveness (0.881), time and place flexibility (0.880), learning interaction (0.893), and availability of learning facilities (0.860) — all demonstrate substantial contributions to the construct. Similarly, for the learning motivation construct, the indicators — learning enthusiasm (0.877), learning independence (0.907), academic responsibility (0.836), and academic goals (0.876) — also exceed the validity threshold, confirming their reliability in measuring the construct. These results confirm that the measurement model meets the standards for indicator validity.

Table 3. Convergent Validity Criteria of Research Variables

Variable	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Blended Learning	0.901	0.931	0.772
Learning Motivation	0.898	0.929	0.765

To assess the quality of the latent constructs in the reflective measurement model, internal reliability and convergent validity were evaluated. Reliability was measured using Cronbach's Alpha and Composite Reliability (CR), while convergent validity was assessed using the Average Variance Extracted (AVE). As shown in Table 3, both constructs demonstrated strong reliability. The blended learning construct recorded a Cronbach's Alpha of 0,901 and a CR of 0,931, while the learning motivation construct recorded a Cronbach's Alpha of 0,898 and a CR of 0,929. All values exceeded the 0,70 threshold, indicating high internal consistency (Hair Jr et al., 2021). For convergent validity, the AVEs for blended learning and learning motivation were 0.772 and 0.765, respectively, both well above the 0.50 minimum. This means that more than half of the variance in the indicators is explained by their respective constructs, confirming that the indicators are valid representations of the constructs. Overall, these results demonstrate that the measurement model fulfills the criteria for both reliability and convergent validity. This ensures that the constructs are measured accurately, providing a robust foundation for the subsequent structural model analysis using PLS-SEM.

Table 4. Discriminant Validity Criteria for Research Variables

Variable	Blended Learning	Learning Motivation
Blended Learning	0.878	
Learning Motivation	0.810	0.875

Discriminant validity was evaluated using the Fornell-Larcker criterion, a widely applied approach in reflective measurement model analysis within PLS-SEM (Hair et al., 2019). This test determines whether each construct is truly distinct from the others in the model. According to Fornell and Larcker (1981), discriminant validity is achieved when the square root of a construct's Average Variance Extracted (AVE) is greater than its correlations with other constructs. As shown in Table 4, the square root of AVE for blended learning was 0.878, and for learning motivation was 0.875, both higher than their inter-construct correlation of 0.810. This confirms that each construct is uniquely measured and that there is no significant overlap in the indicators. These results demonstrate that both blended learning and learning motivation satisfy the Fornell-Larcker criterion for discriminant validity. This provides further assurance that the constructs are distinct, supporting the robustness of the measurement model and its readiness for subsequent structural analysis.

4.3. Structural Model Measurement (Inner Model)

Table 5. Analysis of the Direct Effect of Blended Learning on Learning Motivation

Direct Effect	Path Coefficient	T-Statistics	P-Values
Blended Learning → Learning Motivation	0.810	26.298	0.000

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The results of the structural model analysis, presented in Table 5, indicate that the blended learning variable has a direct, positive, and significant influence on learning motivation. The path coefficient of 0.810 suggests that enhancing the quality of blended learning—through improvements in learning effectiveness, flexibility, interaction, and facilities—directly fosters higher levels of student motivation. This finding is consistent with Self-Determination Theory, which posits that autonomy, competence, and relatedness are critical drivers of motivation (Ryan & Deci, 2000). The T-statistic of 26.298 and the p-value of 0.000 confirm the statistical significance of this relationship at the 5% level, supporting the acceptance of the proposed hypothesis. These findings align with previous studies (Alammary et al., 2014; Rasheed et al., 2020) that highlight the positive impact of blended learning on learner engagement and motivation. Practically, this underscores the importance for educational institutions to integrate well-structured blended learning models, not only to maintain academic quality but also to sustain students' intrinsic motivation in an era of increasing digitalization in education.

Table 6. Coefficient of Determination (R^2) of Learning Motivation

Variable	R Square
Learning Motivation	0.656

The analysis reveals that the learning motivation variable achieved an R-squared (R^2) value of 0.656, indicating that the blended learning construct explains 65.6% of the variance in learning motivation. This demonstrates that the quality of blended learning implementation substantially contributes to enhancing students' motivation. In the context of social sciences, Hair et al. (2021) classify R^2 values between 0.50 and 0.75 as moderate, suggesting that this model has solid predictive power. The remaining variance may be attributed to other factors not examined in this study, such as learning styles, peer interactions, social support, and institutional learning environments. This study advances previous research by providing empirical evidence from a higher education setting in Indonesia, where the integration of blended learning is still in its development stage. Unlike earlier studies that primarily assessed outcomes in fully online or conventional settings, this research explicitly examines a hybrid instructional model using PLS-SEM, which is particularly suited for exploring complex relationships between latent constructs with relatively small to medium sample sizes. The results confirm that blended learning has a direct, positive, and significant effect on students' learning motivation. This finding is consistent with Radovan & Radovan (2024), who reported higher motivation levels among students engaged in blended learning compared to those in traditional classes, emphasizing the importance of time flexibility and multimodal resources in sustaining interest. Similarly, Wei (2024) demonstrated that the effect is more potent when accompanied by adequate digital literacy, highlighting the importance of equipping students with the skills to navigate online learning platforms effectively.

Moreover, Isma et al. (2023) emphasized that interactive instructional design enhances student engagement, while Siregar et al. (2023b) found that blended learning maintained student motivation during the COVID-19 pandemic by offering adaptive flexibility in emergency contexts. However, not all results are uniformly positive; Prihastari and Yustinaningrum (2022) reported moderate motivation levels in mathematics courses, suggesting that subject matter, instructional design quality, and technological readiness can influence outcomes. From a practical perspective, these findings underscore the importance of universities investing in well-designed blended learning systems, offering continuous digital literacy training, and developing interactive course content to maximize motivational benefits. Policymakers should also consider blended learning as part of long-term educational strategies, especially in anticipation of future disruptions or the growing demand for flexible learning modalities. Nevertheless, this study has limitations. The sample was restricted to a single institutional context, and the cross-sectional design limits causal generalization. Future research should incorporate longitudinal data, compare results across multiple institutions, and examine additional moderating variables, such as self-regulation or instructor readiness. Overall, this research reinforces the growing consensus that, when effectively implemented, blended learning can significantly enhance student motivation in higher education. By integrating robust technological infrastructure, engaging pedagogy, and strong institutional support, blended learning can serve as a sustainable and adaptive strategy in the evolving landscape of modern education.

4.4. IPMA Analysis Results

The Importance-Performance Map Analysis (IPMA) was conducted to evaluate respondents' perceptions by mapping the relative importance and performance levels of each indicator in relation to the learning motivation construct. In this analysis, the Y-axis represents the importance value (total effects), while the X-axis represents the performance value for each construct. For interpretive clarity, two reference lines were drawn to indicate the average importance and average performance scores. The resulting map is divided into four quadrants, each representing a combination of high or low importance and performance levels. According to Ringle and Sarstedt (2016), indicators or constructs located in the bottom-right quadrant (Quadrant IV)—which display above-average importance but below-average performance—should be prioritized for improvement, as these areas have the most significant potential to enhance the targeted outcome. The next priority is Quadrant I (high importance and high performance), followed by Quadrant III (low importance and low performance), and finally Quadrant II (low importance and high performance).

The advantage of using IPMA lies in its ability to go beyond statistical significance by incorporating a performance dimension, enabling researchers and practitioners to identify not only the most influential constructs but also those requiring immediate managerial attention. This aligns analytical results with practical decision-making needs, particularly in the context of implementing blended learning to improve student motivation. Table 7 presents the total effect values, performance scores, and average indicator ratings associated with the learning motivation construct. The IPMA results for the blended learning indicators were generated through multiple iterations using SmartPLS 3, ensuring accuracy and robustness in the analysis. These findings offer actionable insights for educators and policymakers to strategically enhance blended learning design strategically, thereby maximizing its motivational impact on students.

Table 7. Results of Importance-Performance Map Analysis (IPMA) of Blended Learning Constructs

Indicator	Importance	Performance	Quadrant
Learning Effectiveness	0.210	53.116	III
Flexibility of Time & Place	0.222	58.340	IV
Learning Interaction	0.230	69.164	I
Availability of Learning Tools	0.218	61.812	II
Average	0.220	60.608	

The results of the Important Performance Map Analysis (IPMA) for the variable level produce the positions of the variables in quadrants I to IV as follows:

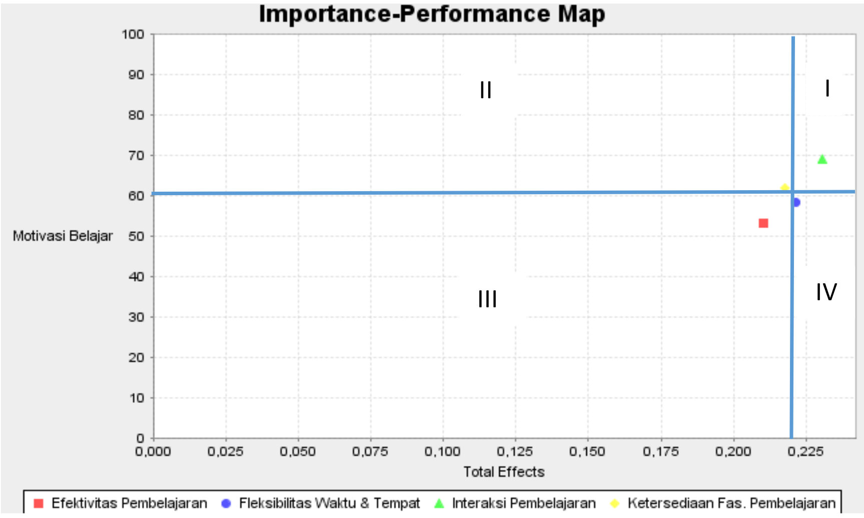

Figure 2. Importance-Performance Map

Based on Figure 2, the distribution of blended learning indicators across the quadrants offers a structured, evidence-based roadmap for improvement.

a. Learning Interaction (Quadrant I): This indicator demonstrates above-average importance and performance. This finding aligns with Isma et al. (2023), who emphasize that strong interaction fosters student engagement and sustained motivation. While already performing well, this area should be preserved and continuously enhanced to maintain its positive impact within the blended learning framework.
b. Availability of Learning Tools (Quadrant II): Located in the high-performance but low-importance quadrant, this indicator shows that while adequate resources are essential, their direct motivational effect is limited compared to pedagogical factors. Similar findings were reported by Fitri et al. (2024). Hence, additional investments in this area may not yield substantial motivational gains.
c. Learning Effectiveness (Quadrant III): This indicator reflects both low importance and low performance. Although its current influence on motivation is modest, neglecting it could hinder long-term blended learning outcomes. Incremental enhancements, such as refining instructional design and integrating formative feedback, can gradually improve its contribution.
d. Flexibility of Time and Place (Quadrant IV): The most critical finding is that this indicator demonstrates high importance but low performance, requiring immediate attention. Enhancing flexibility through adaptive scheduling, diverse learning modalities, and location-independent access directly addresses learners' autonomy needs, identified in Self-Determination Theory as a key driver of intrinsic motivation (Ryan & Deci, 2000). This result diverges from Prihastari and Yustinaningrum (2022), who found that flexibility has less impact in specific contexts, suggesting that its influence may be amplified in higher education environments with stronger digital readiness.

From a practical perspective, these priorities suggest that universities should first focus on improving flexibility, followed by sustaining and enhancing learning interaction. Incremental improvements in learning effectiveness should then be pursued to strengthen its long-term contribution, while maintaining current standards for learning tools. By aligning these improvements with ongoing digital and hybrid education trends, institutions can optimize resource allocation, address critical motivational drivers, and reinforce their competitive position in delivering compelling blended learning experiences.

V. Conclusion

This study demonstrates that the blended learning model has a positive and significant effect on students' learning motivation in the Informatics Engineering Study Program at Universitas Indraprasta PGRI. Integrating face-to-face and online learning, blended learning draws on four core indicators: learning effectiveness, time and place flexibility, availability of learning facilities, and learning interaction, which collectively enhance motivation. The Importance-Performance Map Analysis (IPMA) reveals that, although overall indicator performance is strong, time and place flexibility, as well as learning interaction, stand out as high-importance yet lower-performance areas, making them strategic priorities for improvement. This not only confirms the motivational benefits of blended learning but also illustrates the value of IPMA in identifying targeted enhancements.

Theoretically, the results reinforce self-determination and learner autonomy perspectives, where flexibility and interaction are vital drivers of sustained motivation. Practically, the findings guide higher education institutions in refining their blended learning design, focusing interventions, and allocating resources effectively in line with current digital learning trends. However, the study has limitations. Data were collected from a single institution within a specific time period, which limits the generalizability of the findings. Potential moderating factors, such as prior online learning experience, digital literacy, or socioeconomic background, were not examined. The cross-sectional design also restricts causal inferences. Future research should employ longitudinal approaches, broaden the sample across institutions and disciplines, and explore additional variables, such as technology acceptance, self-regulated learning, and social presence. Comparative studies with entirely online and traditional learning formats could further clarify contextual influences on blended learning effectiveness.

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