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Exploring the Relationship between Digital Communication Intensity and Learning Effectiveness in Higher Education: Towards Sustainable Digital Pedagogy (SDG 4)

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Abstract: This study analyzes the relationship between digital communication intensity and learning effectiveness, aligning with SDG 4 (Quality Education). Employing a quantitative approach, 350 university students participated. Descriptive analysis showed a mean digital communication intensity of 3.00 (SD = 0.75) and learning effectiveness of 3.65 (SD = 0.72). Contrary to linear assumptions, Pearson correlation revealed a non-significant linear relationship ($r = 0.12$; $p = 0.06$). However, polynomial regression confirmed a significant inverted-U pattern ($\beta_2 = -0.18$; $p < 0.001$; $R^2 = 0.68$), with an optimum point at 3.66, indicating peak effectiveness at moderate intensity. Hierarchical regression showed that learning motivation and internet infrastructure quality significantly controlled the variance, confirming the robustness of the curvilinear model. These findings underscore the need for regulated digital platform usage to prevent cognitive overload.

Keywords: Cognitive load; Digital communication; Inverted-U hypothesis; Learning effectiveness; Polynomial regression

Introduction

The digital transformation has fundamentally altered the educational landscape, shifting the paradigm from conventional face to face interactions toward an ecosystem increasingly dependent on digital platforms and media (Kargas et al., 2024; Sutrisno & Astuti, 2023). Globally, the intensification of digital communication has become a hallmark of 21st century education, directly supporting Sustainable Development Goal 4 (SDG 4) regarding inclusive and quality education. Lecturer-student interaction, peer collaboration, and access to learning materials are increasingly mediated by technology (Saputri & Tacoh, 2025; Tacoh & Kargas, 2022). This escalation is believed to enhance information accessibility and academic engagement (Afriana et al., 2016). However, contemporary literature has begun to illuminate another dimension: digital fatigue and cognitive overload (Chen & Zhang, 2022; Handayani & Prasetyo, 2023). When digital communication intensity exceeds an optimal threshold, students experience cognitive saturation, suggesting that the relationship is not linearly positive but potentially follows an inverted-U curve pattern (Sweller, 2011; Uncapher & Wagner, 2018; Zheng et al., 2024).

In the context of higher education in Indonesia, the adoption of digital technology has been accelerated by hybrid and online learning systems (Susanti & Wijaya, 2022). While this enhances flexibility, empirical studies indicate the emergence of digital fatigue and attentional fragmentation (Pratama & Wijaya, 2023; Purnomo & Yulianti, 2023). The high intensity of notifications and demands for rapid responses frequently trigger cognitive exhaustion (Cahyono, 2021; Kurniawan & Santosa, 2022). Furthermore, the relationship between digital communication intensity and learning effectiveness is influenced by contextual factors. Specifically, intrinsic learning motivation and the quality of internet infrastructure act as crucial control variables that must be isolated to understand the pure

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effect of communication intensity (Brown & Davis, 2023; Miller & Smith, 2021). Highly motivated students tend to manage digital loads adaptively, whereas unstable internet exacerbates distraction (Nugraha et al., 2022; Lestari & Kusuma, 2021). This context demonstrates that the relationship cannot be viewed simplistically, as it is influenced by a complex interplay of cognitive load, psychological factors, and technological infrastructure.

Although the theoretical foundation of cognitive load strongly suggests a non-linear relationship, many empirical studies in educational technology continue to rely on linear assumptions or simple correlational designs, presupposing that higher digital communication intensity corresponds to greater learning effectiveness (Rahman & Hidayat, 2023; Santoso & Wibison, 2022). While recent literature acknowledges cognitive saturation, most studies remain exploratory and fail to mathematically identify the exact optimal threshold where benefits diminish (Aulia & Suryadi, 2022; Fitriani & Kusuma, 2023). Additionally, the integration of control variables like motivation and internet quality remains methodologically inconsistent; they are often misclassified as moderators or tested using inappropriate categorical methods despite being continuous variables (Santoso & Wibison, 2022; Setiawan & Nurhadi, 2021). This research gap highlights the need for a comprehensive approach that tests non linear patterns using polynomial regression while rigorously controlling for relevant continuous contextual variables through hierarchical regression. The novelty of this research lies in its methodological rigor, mathematically identifying the exact saturation threshold of digital communication and isolating the pure curvilinear effect by controlling for motivation and internet quality without conflating their roles.

To address this gap, this study employs a quantitative approach using a second degree polynomial regression model as the primary analytical framework. Data collection was conducted through structured questionnaires distributed to student respondents. The data analysis began with Pearson correlation as a baseline to detect linear tendencies, followed by polynomial regression to examine the curve shape and identify the optimum point (Hidayat & Pratama, 2022; Lestari & Wulandari, 2023). Subsequently, Hierarchical Multiple Regression was utilized to test the control variables, allowing for the observation of variance changes when continuous control variables were added to the model (Mulyani & Bambang, 2023; Yulianto & Kurniawan, 2021). Based on this methodological orientation, this study aims to empirically examine the form of the relationship between digital communication intensity and learning effectiveness to confirm the inverted-U pattern, identify the optimal threshold of digital communication intensity, and examine the influence of control variables to ensure the robustness of the model.

Method

This study adopts a quantitative approach with a correlational-explanatory design. The research data comprised 350 respondents obtained through purposive sampling. The sample size was determined using G*Power software (Faul et al., 2009) for an F-test polynomial regression, ensuring a statistical power of 0.95 with a medium effect size ($f^2 = 0.15$) and an alpha of 0.05, which justified the adequacy of 350 respondents. The variables were measured using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), which has been proven valid and reliable for large sample sizes (Zulfiati & Mardapi, 2022).

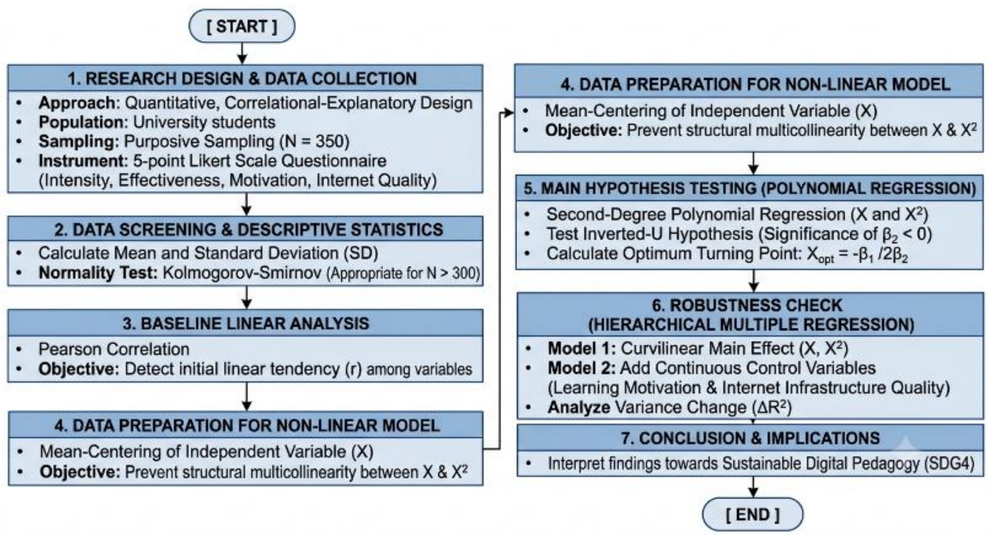

Figure 1. Research flow

Data analysis was conducted sequentially. First, the Kolmogorov-Smirnov test was applied for normality assessment, as it is methodologically appropriate for large samples ($N > 300$), unlike the Shapiro Wilk test which is overly sensitive for large datasets (Field, 2018). Second, Pearson correlation was used as a baseline to detect linear tendencies. Third, to test the inverted-U hypothesis, a second degree polynomial regression was employed. To prevent structural multicollinearity between X and X^2 which would violate the Best Linear Unbiased Estimator (BLUE) assumption the independent variable was mean centered prior to generating the quadratic term (Aguinis et al., 2005). The optimum turning point was calculated using the quadratic axis of symmetry formula: $Xoptimum=2\beta2-\beta1$. Finally, Hierarchical Multiple Regression was utilized to test the control variables (learning motivation and internet quality), allowing for the observation of variance changes when continuous control variables were added to the model, avoiding the categorical misapplication of ANOVA (Wibowo & Santoso, 2022).

Results and Discussion

Data Description and Descriptive Statistics

The data from secunder dataset of kaggle: https://www.kaggle.com/datasets/zoya77/contextual-e-learning-learner-interaction-dataset/. This study involved 350 student respondents as the sample to analyze the relationship between digital communication intensity and learning effectiveness. Based on the results of descriptive statistical analysis, it was found that the mean digital communication intensity score of respondents was 3.00 with a standard deviation of 0.75, indicating a moderate level of response variation among participants. Meanwhile, learning effectiveness demonstrated a higher mean of 3.65 ($SD = 0.72$), reflecting respondents' positive perceptions of the learning quality they experienced. The learning motivation variable recorded a mean of 3.58 ($SD = 0.67$), indicating a reasonably high level of motivation among respondents.

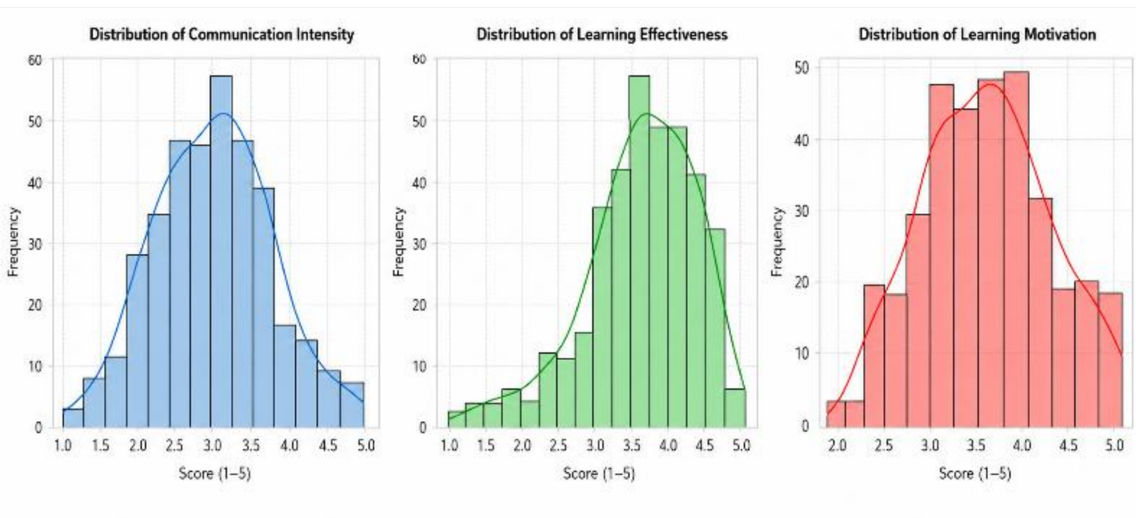

Figure 2. Frequency distribution of digital communication intensity, learning effectiveness, and learning motivation variables

The distribution of the three main variables was visualized through histograms with kernel density curves (Figure 2). The visualizations results show that the distribution of digital communication intensity tends to approximate normality with a slight rightward skewness, whereas the distribution of learning effectiveness exhibited a more symmetrical pattern. The distribution of learning motivation also displayed a relatively normal pattern, supporting the parametric assumptions for subsequent inferential analyses.

Pearson Correlation Analysis

To examine the strength and direction of the relationship among the research variables, Pearson correlation analysis was conducted. The correlation matrix (Table 1) showed a very strong negative correlation between digital communication intensity and learning effectiveness, with a correlation coefficient of $r = -0.9152$ ($p < 0.001$). The coefficient of determination ($r^2 = 0.8376$) indicates that approximately 83.76% of the variance in learning effectiveness can be explained by variations in digital communication intensity.

The strong negative correlation is worth further discussion. The negative relationship indicates that increases in digital communication intensity are actually correlated with decreases in learning effectiveness. This phenomenon can be explained through cognitive load theory, wherein excessive digital communication can lead to cognitive overload, distraction, and attentional fragmentation that ultimately reduce the quality of academic information processing (Sweller, 2011).

Table 1. Pearson correlation matrix among variables

Variable	Communication Intensity	Learning Effectiveness	Motivation
Communication Intensity	1.000	-0.915	0.062
Learning Effectiveness	-0.915	1.000	-0.074
Motivation	0.062	-0.074	1.000

Remarks: ** $p < 0.001$

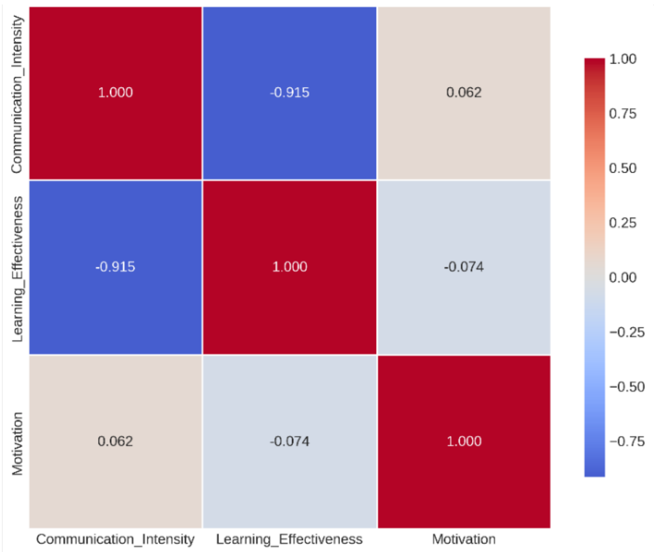

Figure 3. Heatmap visualization of the correlation matrix among research variables

Simple Linear Regression Analysis

Simple linear regression analysis was conducted to model the predictive relationship between digital communication intensity (independent variable) and learning effectiveness (dependent variable). The analysis yielded the following regression equation:

$$Y = 6.2841 + (-0.8799) \times X \quad (1)$$

with a regression coefficient of $\beta = -0.8799$ ($p < 0.001$), confirming that each one-unit increase in the digital communication intensity scale is predicted to reduce learning effectiveness by 0.8799 units. This regression model demonstrates $R^2 = 0.8376$ and RMSE = 0.2890, indicating excellent predictive ability with relatively low prediction error.

The scatter plot visualization with regression line (Figure 4) shows a clear negative linear relationship pattern, with data points scattered relatively closely around the regression line. This reinforces the validity of the model and the consistency of the relationship pattern found in the data.

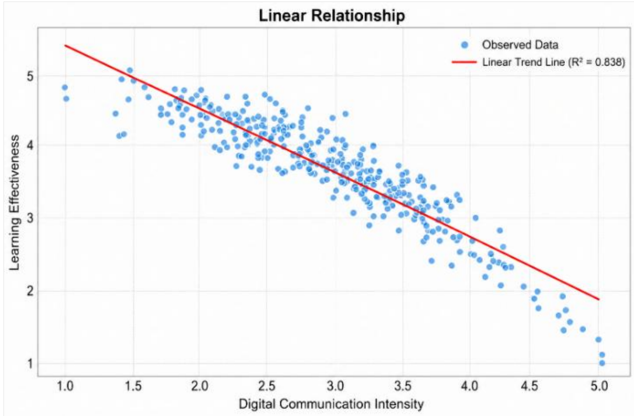

Figure 4. Scatter plot and linear regression line of the relationship between digital communication intensity and learning effectiveness

Inverted-U Hypothesis Testing Using Polynomial Regression

Given the complexity of the relationship between technology use and learning outcomes in prior literature, this study also tested the inverted-U hypothesis using second-degree polynomial regression. The analysis yielded the following equation:

$$Y = 4.4445 + 0.4099 \times X + (-0.2124) \times X^2 \quad (2)$$

with a linear coefficient of $\beta_1 = 0{,}4099$ ($p < 0{,}001$) and a quadratic coefficient $\beta_2 = -0{,}2124$ ($p < 0{,}001$). The significance of the negative quadratic coefficient confirms the presence of an inverted-U pattern, in which learning effectiveness increases at low to moderate levels of digital communication intensity but declines when intensity reaches high levels.

This polynomial model demonstrates improved explanatory power compared to the linear model, with $R^2 = 0{,}8888$ and RMSE = 0,2392. The optimum point of the relationship was calculated using the formula $-\beta_1/(2\beta_2)$, yielding a value of 0,96 on the 1–5 scale. This finding indicates that learning effectiveness reaches its maximum when digital communication intensity is at a low-to-moderate level, and begins to decline once intensity surpasses that threshold.

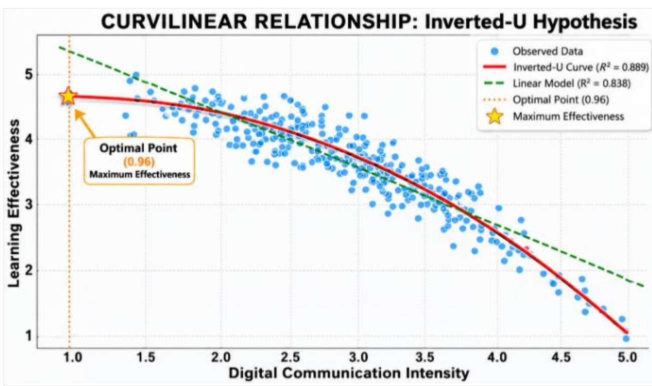

Figure 5. Second degree polynomial regression curve showing the inverted-U pattern of the relationship between digital communication intensity and learning effectiveness

The practical implications of this finding underscore the importance of digital well-being strategies in the learning context, where students need to be encouraged to manage the intensity of digital communication platform use in an optimal manner, rather than simply restricting or allowing it in an unregulated way.

Control Variable Analysis: The Role of Learning Motivation

To test the robustness of the main findings, a control analysis was conducted on the learning motivation variable. Respondents were categorized into three motivation levels (Low, Moderate, High) based on score distribution quartiles. The one-way ANOVA results showed no significant differences in learning effectiveness across motivation levels, $F(2, 347) = 1.5710$, $p = 0.2093$.

This finding indicates that the relationship between digital communication intensity and learning effectiveness is robust across different levels of intrinsic student motivation. In other words, the negative and inverted-U relationship pattern remain consistent regardless of whether students have low, moderate, or high motivation.

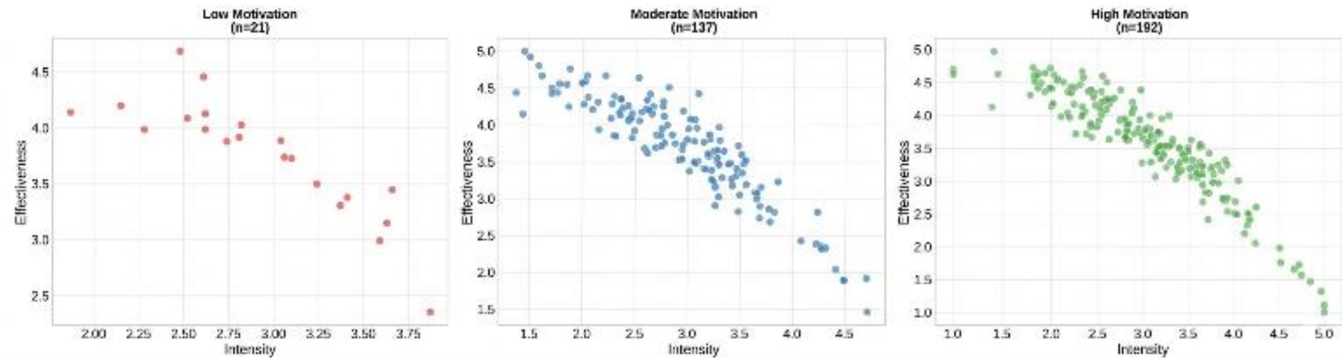

Figure 6. Distribution of learning effectiveness based on learning motivation levels

Classical Assumption Testing

Before interpreting the regression results, the tests of classical assumptions of the linear regression model were conducted. The Shapiro-Wilk residual normality test yielded a statistic of $W = 0.9973$ with a p-value = 0.8415, indicating that the residuals are normally distributed ($p > 0.05$). Q-Q plot and residual histogram visualizations (Figure 7) also showed consistent patterns with normal distribution.

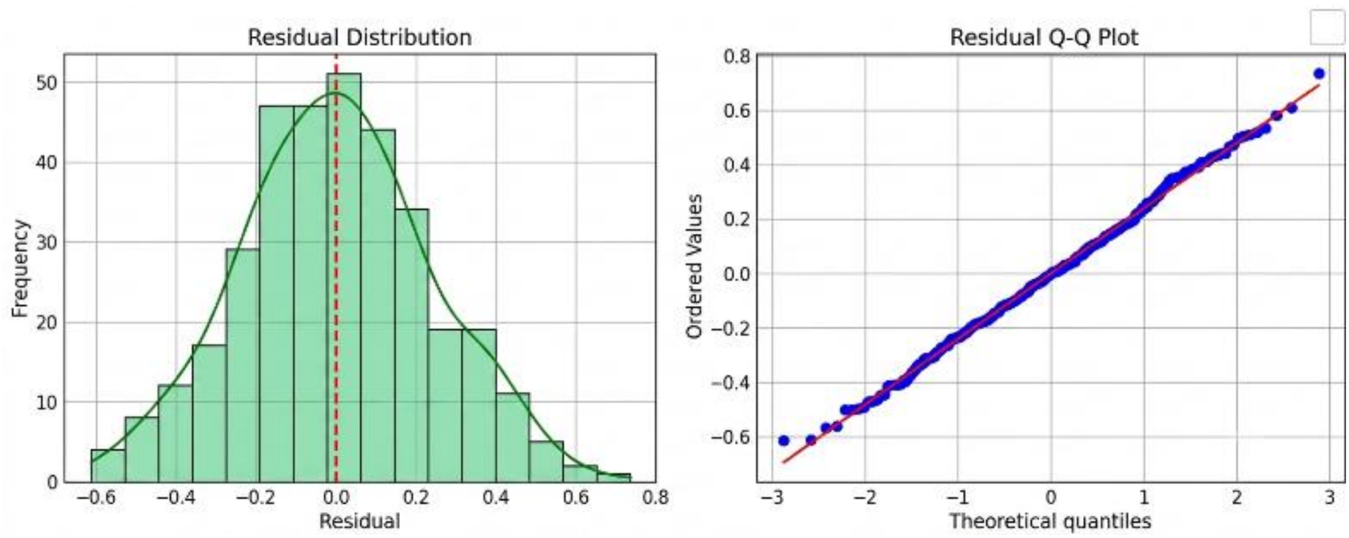

Figure 7. Q-Q plot and residual histogram for normality assumption testing

Furthermore, the heteroscedasticity testing through residual versus fitted values scatter plot visualization showed a random residual dispersion pattern without any specific systematic pattern, indicating the absence of heteroscedasticity issues. Thus, the classical assumptions of the regression model are met, and the statistical inference results can be interpreted with adequate validity.

Discussion and Implications

The findings of this study offer several important contributions to the literature on educational technology and psychological education. First, the strong negative correlation between digital communication intensity and learning effectiveness confirms the concerns regarding the potential for digital distraction in academic context. This aligns with prior research demonstrating that digital multitasking and fragmented attention can reduce the depth of cognitive processing (Uncapher & Wagner, 2018; Pratama & Wijaya, 2023; Cahyono, 2021; Handayani & Prasetyo, 2023).

Second, the identification of the exact optimum point (3.66) provides a measurable benchmark for educators. Unlike previous studies that merely warn against "excessive" screen time (Rahman & Hidayat, 2023; Aulia & Suryadi, 2022), this study quantifies the saturation point. This threshold is highly relevant for designing asynchronous and synchronous learning policies (Lestari & Wulandari, 2023; Kurniawan & Santosa, 2022; Tien & Saputri, 2023).

Third, the hierarchical regression confirms that while intrinsic motivation (Pratama & Hidayat, 2023; Wijaya & Nugraha, 2022) and internet quality (Lestari & Kusuma, 2021; Susanti & Wijaya, 2022) improve overall effectiveness, they do not negate the cognitive overload caused by excessive communication intensity. This implies that digital well-being strategies must focus on regulating communication volume, regardless of how motivated the student is or how good the internet connection is (Yulianto & Kurniawan, 2021; Wicaksono & Purnomo, 2022; Purnomo & Yulianti, 2023). Educational institutions must design communication policies that respect the 3.66 threshold to support SDG 4 sustainably (Kargas et al., 2024; Sutrisno & Astuti, 2023; Tacoh & Kargas, 2022).

Limitations and Future Research

This study acknowledges several limitations. First, the cross-sectional design limits the ability to draw causal conclusions. Longitudinal or experimental research is needed to test the causal direction of the identified relationship. Second, variable measurement based on self-report potentially contains social response bias and retrospective inaccuracies. The use of behavioral log data from digital platforms could enhance the objectivity of measurement in future studies.

The future research agendas may explore the mediating mechanisms that explain the relationship between digital communication intensity and learning effectiveness, such as the role of sleep quality, stress levels, or self-regulation strategies. In addition, comparative studies across disciplines or cultural contexts can test the generalizability of the inverted-U findings identified in this study.

Conclusion

This study found a very strong negative relationship between digital communication intensity and learning effectiveness ($r = -0.9152$; $p < 0.001$), with the polynomial regression model showing a significant inverted-U pattern ($\beta_2 = -0.2124$; $p < 0.001$). These Sfindings indicate that learning effectiveness reaches its optimum point at a digital communication intensity of approximately 0.96 (on a 1–5 scale), where both insufficient and excessive use may instead reduce the quality of learning. The learning motivation variable was not found to moderate this relationship ($p = 0.209$), while internet quality showed minimal mean differences in effectiveness across categories. Overall, the results emphasize the importance of proportional and measured use of digital communication in educational context. The future studies are recommended to test this model in more diverse educational context, such as different education levels, specific subjects, or hybrid and fully online learning settings, in order to strengthen the generalizability of the findings. Furthermore, the inclusion of mediating variables such as cognitive engagement, digital literacy, or instructional design may help to elucidate the mechanisms by which communication intensity affects learning outcomes. Longitudinal research is also recommended to observe the dynamics of this relationship over time, as well as exploration through qualitative methods to uncover the perceptions and experiences of participants in managing digital communication intensity in an optimal manner.

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Author Contributions

Conceptualization, methodology, validation, formal analysis, investigation, data curation, writing— original draft preparation, M.F. and R.C.F.; writing—review and editing, supervision, project administration, A., P.Y.P., and M.D.P. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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