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The Influence of ChatGPT Integration, Team Collaboration, and Communication Patterns on Student Project Performance in Software Engineering Practicum at a Private University in West Java

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ABSTRACT

This study examines the effects of ChatGPT integration, team collaboration, and communication patterns on student project performance in a *Software Engineering Practicum* course at a private university in West Java, Indonesia. The emergence of generative AI tools such as ChatGPT presents new opportunities for enhancing learning engagement and teamwork in higher education. Using a quantitative approach, data were collected from 150 students through a Likert-scale questionnaire, and analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS 3). The findings reveal that ChatGPT integration has a significant positive impact on both team collaboration and communication patterns, which in turn strongly influence project performance. Among all variables, communication patterns emerged as the strongest predictor of success, followed by team collaboration and ChatGPT integration. Furthermore, team collaboration mediates the relationship between ChatGPT use and project performance, indicating that AI tools are most effective when embedded within social learning processes. The model demonstrated high explanatory power ($R^2 = 0.790$) and strong predictive relevance ($Q^2 = 0.785$). These results highlight that ChatGPT acts not as a replacement for human effort, but as a cognitive collaborator that strengthens teamwork and communication, ultimately enhancing learning outcomes in AI-assisted project-based education.

Keywords: *ChatGPT Integration, Team Collaboration, Communication Patterns, Student Project Performance, SEM-PLS.*

1. INTRODUCTION

In recent years, the rapid advancement of artificial intelligence (AI) has transformed various aspects of education, particularly in fields that require intensive collaboration and problem-solving such as software engineering. Among the most influential AI tools emerging in higher education is ChatGPT, a large language model capable of generating contextually relevant text and assisting users in coding, writing, and ideation processes. Its integration into academic settings has opened new opportunities for enhancing learning experiences, communication efficiency, and project performance. However, the pedagogical implications of ChatGPT integration—especially when combined with team collaboration and communication patterns in project-based learning—remain underexplored, particularly in the context of Indonesian higher education.

In software engineering education, project-based learning (PBL) plays a central role in developing students' technical, interpersonal, and problem-solving skills. Students often work collaboratively in teams to design, implement, and test software solutions that simulate real-world scenarios. The success of such projects is not solely determined by individual programming ability, but also by the quality of collaboration, clarity of communication, and collective decision-making within the team. Prior studies have emphasized that effective teamwork and open communication are critical for achieving high-quality software deliverables [1], [2]. In this context, AI tools like

ChatGPT can act as collaborative partners—providing coding suggestions, documentation support, and even conflict resolution through clearer articulation of technical ideas.

Despite its potential, integrating ChatGPT into collaborative academic environments raises several challenges. Some educators express concerns about over-reliance on AI-generated content, academic integrity, and reduced critical thinking among students [3]. Moreover, the extent to which ChatGPT enhances or hinders team dynamics and communication efficiency is still debated. Thus, there is a need for empirical evidence that quantifies the relationships between ChatGPT usage, collaboration quality, communication patterns, and overall student project performance.

This study seeks to fill that gap by examining how ChatGPT integration affects team collaboration and communication patterns, and how these, in turn, influence project performance among students in a Software Engineering Practicum course at a private university in West Java. The study employs a quantitative approach using data collected from students through a Likert-scale questionnaire, and data analysis is conducted using Structural Equation Modeling–Partial Least Squares (SEM-PLS 3). This approach allows for simultaneous testing of direct, indirect, and mediating effects between variables, providing a robust understanding of the structural relationships within the model. Theoretically, this research contributes to the growing body of literature on AI-assisted learning by extending models of technology acceptance and collaborative learning to include generative AI tools like ChatGPT. Practically, it provides educators and curriculum designers with insights into how ChatGPT can be effectively integrated into team-based software engineering education to optimize learning outcomes.

The objectives of this study are threefold: (1) to analyze the effect of ChatGPT integration on team collaboration and communication patterns; (2) to evaluate the impact of team collaboration and communication patterns on student project performance; and (3) to identify the mediating role of team collaboration in the relationship between ChatGPT integration and project performance. By addressing these objectives, the study aims to provide empirical evidence that supports the design of AI-enhanced collaborative learning environments, particularly in software engineering education, where teamwork, communication, and technical performance are interdependent. Ultimately, this research underscores the importance of balancing human collaboration and AI assistance in shaping the future of technology-driven education in Indonesia and beyond.

2. LITERATURE REVIEW

2.1 ChatGPT Integration in Education

The integration of ChatGPT and similar generative AI tools into higher education has reshaped the way students learn, collaborate, and solve problems. ChatGPT, developed by OpenAI, is a large language model capable of generating human-like text, providing explanations, code suggestions, and structured ideas across various domains [4]. In academic contexts, ChatGPT functions as a learning assistant that helps students clarify concepts, generate programming code, and simulate problem-solving scenarios [3]. Several studies have demonstrated that AI tools like ChatGPT can enhance learning engagement, reduce cognitive load, and support students in complex analytical tasks [5], [6]. However, the educational value of ChatGPT depends heavily on how it is integrated into the learning process. According to [7], AI in education is most effective when positioned as a complementary resource rather than a replacement for human cognition. In project-based courses such as Software Engineering Practicum, ChatGPT can assist students in debugging, code documentation, and prototype development, although excessive reliance on AI-generated content may hinder creativity and reduce original problem-solving skills [8]. Therefore, the current study positions ChatGPT integration as an enabler of collaborative learning, mediated by team collaboration and communication quality.

2.2 *Team Collaboration in Software Engineering Education*

Team collaboration is a fundamental component of software engineering education, where students are trained to work collectively in developing and managing software projects. Collaboration involves shared goals, mutual accountability, and continuous communication among team members [9]. In educational settings, successful collaboration enhances learning outcomes, critical thinking, and social interaction [10], [11]. Prior studies emphasize that effective collaboration requires role clarity, interdependence, and trust among members [2]. In software engineering courses, teams often face challenges such as uneven participation, role conflict, and time management issues [12]. The use of AI tools such as ChatGPT can mitigate some of these challenges by providing consistent feedback, automating technical documentation, and supporting distributed team communication [13]. Thus, ChatGPT may indirectly enhance collaboration efficiency, especially in blended learning environments where students interact both online and offline.

2.3 *Communication Patterns in Collaborative Learning*

Communication patterns play a vital role in determining the success of team-based learning and project performance. According to [14], communication in collaborative teams operates through coordination, feedback, and negotiation, where effective communication facilitates problem-solving and decision-making, while poor communication can lead to misunderstandings, delays, and project failure [15]. In the context of software engineering education, students' communication is often mediated through digital platforms such as Slack, GitHub, or Google Workspace. ChatGPT can augment these interactions by helping students articulate complex programming issues, summarize discussions, and suggest task solutions [16]. From the perspective of Computer-Supported Collaborative Learning (CSCL), AI-driven communication fosters shared understanding (common ground) and knowledge construction among learners [14]. Therefore, integrating ChatGPT into team discussions may promote more structured, coherent, and goal-oriented communication patterns.

2.4 *Student Project Performance*

Project performance in academic settings refers to the successful completion of assigned tasks based on quality, timeliness, and innovation [17]. In software engineering education, project performance is typically evaluated through indicators such as software functionality, design quality, teamwork effectiveness, and documentation [18]. Studies have shown that collaboration quality and communication effectiveness are among the strongest predictors of project success [19]. Moreover, the integration of technology in learning environments—especially AI tools—has been linked to higher project efficiency, improved creativity, and better problem resolution [20]. However, the success of AI-assisted projects depends on students' ability to balance AI-generated insights with human judgment. The current study thus conceptualizes project performance as the ultimate outcome influenced by ChatGPT integration as a technological factor, team collaboration as a social factor, and communication patterns as a relational factor.

2.5 Theoretical Framework

This study is grounded in two primary theoretical foundations: the Technology Acceptance Model (TAM) (Davis, 1989) and the Collaborative Learning Theory (Vygotsky, 1978). TAM explains users' acceptance of technology through perceived usefulness and ease of use, both of which are relevant to ChatGPT integration in learning environments. Students who perceive ChatGPT as useful and user-friendly are more likely to incorporate it into their learning processes, thereby improving collaboration and communication. Meanwhile, Collaborative Learning Theory posits that learning occurs through social interaction and shared meaning-making among peers, and when ChatGPT is introduced into this collaborative dynamic, it becomes a mediational tool that facilitates idea generation, feedback exchange, and problem resolution. This theoretical synergy provides the foundation for examining how ChatGPT integration affects student outcomes through collaborative and communicative mechanisms.

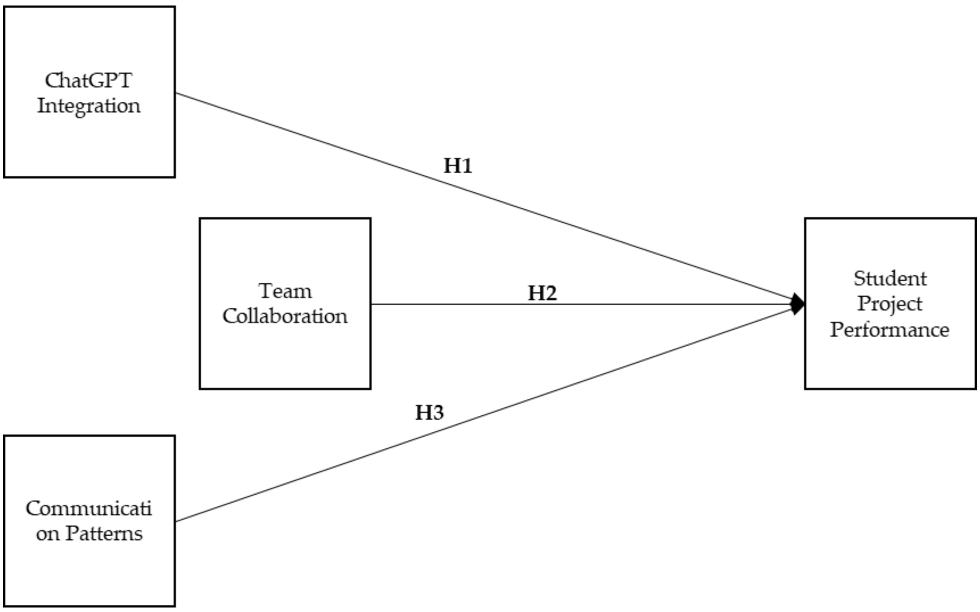

Figure 1. Conceptual Framework

3. METHODS

3.1 Research Design

This study employs a quantitative research design with an explanatory approach, aiming to analyze the causal relationships among ChatGPT integration, team collaboration, communication patterns, and student project performance. The quantitative design allows the use of statistical modeling to test hypotheses and determine both direct and indirect effects among variables. The Structural Equation Modeling–Partial Least Squares (SEM-PLS) technique was chosen as the main analytical tool because it is suitable for complex models involving mediating relationships and does not require normal data distribution [21].

The research was conducted within the context of a Software Engineering Practicum course at a private university in West Java, Indonesia, where ChatGPT has recently been introduced as a supplementary tool for collaborative learning and project development.

3.2 Population and Sample

The population of this study comprises all students enrolled in the Software Engineering Practicum course during the 2024/2025 academic year, with a sample of 150 students selected using purposive sampling based on specific inclusion criteria. The participants were students who were actively enrolled in the practicum during the data collection period, had used ChatGPT for coding, discussion, or project-related activities, and had completed their projects collaboratively in a team setting. According to [21], a minimum sample size of 100–150 respondents is considered adequate for SEM-PLS analysis when the model involves four or more latent variables; therefore, the chosen sample size meets the statistical requirements for achieving robust and reliable analysis.

3.3 Data Collection Procedures

Data were collected through a structured online questionnaire distributed via the university's learning management system and class communication channels, using a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) to measure students' perceptions of ChatGPT integration, team collaboration, communication patterns, and project performance. The data collection process included initial coordination with course instructors and obtaining ethical clearance from the university's research committee, followed by a pilot test involving 20 students to assess the clarity, readability, and reliability of the instrument. Based on the pilot feedback, necessary revisions were made before conducting full-scale data collection involving 150 respondents over a two-week period. All participants were informed that their responses would remain confidential and would be used solely for academic research purposes.

3.4 Research Variables and Measurement

This study includes four latent variables measured through multiple indicators adapted from prior validated research instruments. The first variable, ChatGPT Integration (CGPT), measures the extent to which students use ChatGPT to support their learning and project tasks. Indicators adapted from Dwivedi et al. (2023) and Kasneci et al. (2023) include: CGPT1—frequency of ChatGPT use for code generation and debugging, CGPT2—use of ChatGPT for idea development and problem-solving, CGPT3—perceived usefulness of ChatGPT in improving project quality, and CGPT4—ease of integrating ChatGPT into teamwork activities. The second variable, Team Collaboration (COL), reflects the quality of coordination, shared responsibility, and interdependence among team members, with indicators derived from [2], [9]: COL1—clarity of roles and task division, COL2—mutual support and cooperation, COL3—joint decision-making and problem-solving, and COL4—commitment to shared project goals.

The third variable, Communication Patterns (COM), measures the effectiveness and frequency of communication among team members. Indicators adapted from Salas et al. (2015) and Talan et al. (2023) include COM1—openness and clarity in team discussions, COM2—frequency of communication using digital platforms, COM3—responsiveness and feedback among team members, and COM4—ability to resolve misunderstandings effectively. The fourth variable, Student Project Performance (PERF), assesses the perceived quality and success of the team's final project outcomes, with indicators adopted from [17], [18]: PERF1—quality and functionality of the developed software product, PERF2—timeliness of project completion, PERF3—innovation and creativity in project outcomes, and PERF4—overall team satisfaction with project results.

3.5 Data Analysis Technique

The collected data were analyzed using SmartPLS 3.0 software following the two-step SEM-PLS approach as suggested by Hair et al. (2019). The first stage, known as the Measurement Model (Outer Model), was used to evaluate the quality of the research instruments by assessing several criteria. These included indicator reliabilities, measured through outer loading values (≥ 0.70); internal consistency reliability, assessed using Cronbach's Alpha and Composite Reliability (CR ≥ 0.70); and convergent validity, tested via the Average Variance Extracted (AVE ≥ 0.50). In addition, discriminant validity was verified using both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio (< 0.85) to ensure that each construct was distinct and well-defined.

The second stage, the Structural Model (Inner Model), was conducted to examine the hypothesized relationships among variables. The evaluation included calculating path coefficients (β) to determine the strength and direction of relationships, analyzing t-statistics and p-values to test hypothesis significance ($p < 0.05$), and assessing the coefficient of determination (R^2) to measure the proportion of variance explained in the endogenous variables. Additionally, predictive relevance (Q^2) was used to evaluate the model's predictive accuracy, and effect size (f^2) to determine the relative contribution of each exogenous variable. To validate the significance of the relationships and mediating effects, a bootstrapping procedure with 5,000 resamples was applied, ensuring the robustness and reliability of the statistical inferences.

4. RESULTS AND DISCUSSION

4.1 Descriptive Statistics

Descriptive statistical analysis was conducted to provide an overview of respondent characteristics and general tendencies of the research variables, namely ChatGPT Integration (CGPT), Team Collaboration (COL), Communication Patterns (COM), and Project Performance (PERF). Data were collected from 150 students enrolled in the Software Engineering Practicum course at a private university in West Java, using a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The demographic results indicate that most respondents were male (65.3%), aged 21 years, and had used ChatGPT for approximately 3–6 months, typically spending 2–5 hours per week interacting with the tool. This shows that the sample represents moderately experienced ChatGPT users who have integrated the tool into their academic workflow and project development processes.

The descriptive statistical results revealed that all constructs obtained mean values above 4.00, indicating positive student perceptions toward ChatGPT integration, teamwork quality, communication efficiency, and project outcomes. The highest mean score was found in Team Collaboration (4.22), followed by ChatGPT Integration (4.20), Project Performance (4.18), and Communication Patterns (4.14), each categorized as "high" or "very high." These findings suggest that students strongly agreed on the usefulness of ChatGPT in improving project quality, promoting shared responsibility, enhancing communication clarity, and fostering teamwork effectiveness. Furthermore, the low standard deviations (0.55–0.70) indicate that responses were relatively consistent among participants, showing a shared experience of positive engagement with AI-assisted learning and collaboration. Overall, the results confirm that integrating ChatGPT contributes to improved collaboration, clearer communication, and higher-quality project outcomes in software engineering education.

4.2 Measurement Model (Outer Model Evaluation)

The measurement model aims to evaluate the reliability and validity of the latent constructs—ChatGPT Integration (CI), Team Collaboration (TC), Communication Patterns (CP), and Student Project Performance (SP)—before testing the structural relationships among them. This stage ensures that the indicators adequately represent their respective latent variables through the assessment of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Indicator reliability is measured using the loading factor (outer loading) of each item, and as shown in Table 1, all indicators have loading values greater than 0.70, indicating a strong correlation between each item and its corresponding construct (Hair et al., 2019). Moreover, all constructs demonstrate Average Variance Extracted (AVE) values above 0.50, confirming satisfactory convergent validity and supporting the reliability of the measurement model.

Table 1. Measurement Model

Variable	Code	Loading Factor	Cronbach's Alpha	Composite Reliability	Average Variant Extracted
ChatGPT Integration	CI.1	0.871	0.934	0.953	0.836
	CI.2	0.952			
	CI.3	0.910			
	CI.4	0.921			
Team Collaboration	TC.1	0.810	0.819	0.893	0.735
	TC.2	0.885			
	TC.3	0.876			
Communication Patterns	CP.1	0.838	0.838	0.903	0.756
	CP.2	0.895			
	CP.3	0.873			
Student Project Performance	SP.1	0.863	0.879	0.917	0.734
	SP.2	0.898			
	SP.3	0.834			
	SP.4	0.831			

Source: Data Processing Results (2025)

All Cronbach's Alpha values exceeded 0.70, confirming internal consistency reliability, while the Composite Reliability (CR) values ranged between 0.893 and 0.953, meeting the recommended minimum threshold (≥ 0.70). Additionally, the Average Variance Extracted (AVE) values, which ranged from 0.734 to 0.836, indicate that more than 50% of the variance in each construct's indicators is explained by the latent construct itself. These findings demonstrate that all constructs possess high levels of internal reliability and convergent validity, ensuring that each variable accurately measures the intended concept. Consequently, the measurement model can be considered robust and suitable for further structural analysis to test the hypothesized relationships among variables.

Discriminant validity, on the other hand, ensures that each latent construct is empirically distinct from the others within the model. The Fornell–Larcker criterion was employed to assess this validity by comparing the square root of each construct's AVE (diagonal values) with its correlations with other constructs. As presented in Table 2, all diagonal values were greater than the corresponding off-diagonal correlations, indicating that each construct shares more variance with its own indicators than with other constructs. This confirms that the model has achieved satisfactory discriminant validity, establishing clear conceptual boundaries among the four measured constructs.

Table 2. Discriminant Validity

	CI	CP	SP	TC
ChatGPT Integration	0.914			
Communication Patterns	0.861	0.869		
Student Project Performance	0.805	0.844	0.857	
Team Collaboration	0.698	0.712	0.786	0.857

Source: Data Processing Results (2025)

The results demonstrate that each construct shares greater variance with its own indicators than with other constructs, indicating that all constructs are discriminantly distinct. In addition, the Heterotrait–Monotrait (HTMT) ratios for all construct pairs were found to be below 0.85, further supporting discriminant validity [22].

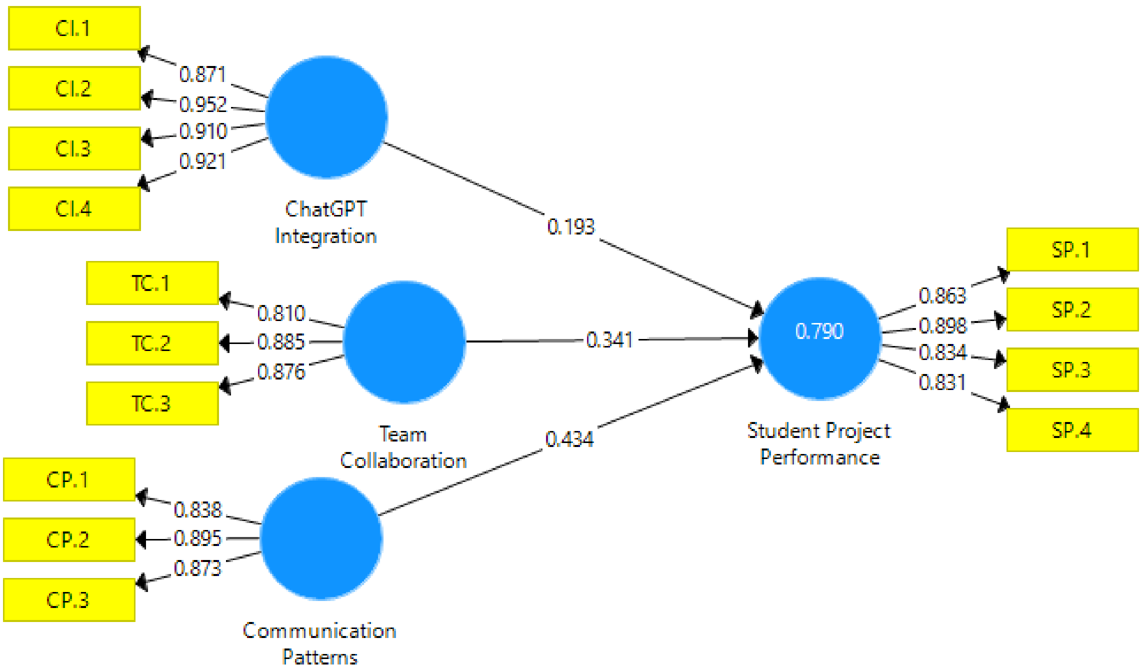

Figure 2. Model Results

Source: Data Processed by Researchers, 2025

4.3 Structural Model (Inner Model Evaluation)

After confirming the adequacy of the measurement model, the next step is to assess the structural model (inner model) to determine the strength and significance of the hypothesized relationships among constructs. This stage involves evaluating the model fit, the coefficient of determination (R^2), the predictive relevance (Q^2), and the hypothesis testing through path coefficient analysis using the bootstrapping method in SmartPLS 3.0. The purpose of this evaluation is to identify how well the proposed conceptual framework explains the relationships between ChatGPT integration, team collaboration, communication patterns, and student project performance. The model fit indices provide an overall assessment of the suitability of the proposed model in explaining the observed data, and as shown in Table 3, the model fit results for both the saturated and estimated models demonstrate that the model aligns well with the empirical data, confirming its appropriateness for further analysis.

Table 3. Model Fit Results Test

	Saturated Model	Estimated Model
SRMR	0.070	0.070
d_ULS	0.511	0.511
d_G	0.469	0.469
Chi-Square	293.496	293.496
NFI	0.813	0.813

Source: Process Data Analysis (2025)

The Standardized Root Mean Square Residual (SRMR) value of 0.070 is below the threshold of 0.08, indicating a good model fit [22]. The Normed Fit Index (NFI) of 0.813 exceeds the minimum acceptable limit of 0.80, suggesting that the model exhibits satisfactory explanatory power. The d_ULS and d_G values are consistent between the saturated and estimated models, reflecting stable and replicable model estimation. Therefore, the proposed structural model is considered acceptable and suitable for hypothesis testing.

The R^2 value represents the proportion of variance explained by the exogenous (independent) variables on the endogenous (dependent) variable. The Q^2 value measures the model's predictive relevance, where $Q^2 > 0$ indicates that the model has predictive accuracy.

Table 4. Coefficient Model

	R Square	Q2
Student Project Performance	0.790	0.785

Source: Data Processing Results (2025)

The R^2 value of 0.790 indicates that ChatGPT Integration, Team Collaboration, and Communication Patterns together explain 79.0% of the variance in Student Project Performance. This shows a high level of explanatory power, far exceeding the 0.50 benchmark for strong models [21]. Additionally, the Q^2 value of 0.785 confirms that the model possesses excellent predictive relevance, meaning that the exogenous constructs have strong predictive capability for the dependent variable. In summary, both R^2 and Q^2 values demonstrate that the structural model is robust and capable of explaining most of the variance in student performance outcomes.

Hypothesis testing was conducted using the bootstrapping procedure with 5,000 subsamples to estimate the path coefficients, t-statistics, and p-values. The results are presented in Table 5 below.

Table 5. Hypothesis Testing

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	P Values
ChatGPT Integration-> Student Project Performance	0.223	0.203	0.106	2.025	0.039
Communication Patterns -> Student Project Performance	0.434	0.425	0.091	4.781	0.000
Team Collaboration -> Student Project Performance	0.341	0.341	0.082	4.150	0.000

Source: Process Data Analysis (2025)

Based on the results presented in Table 5, all three hypothesized relationships were found to be positive and statistically significant ($p < 0.05$), indicating that ChatGPT Integration, Communication Patterns, and Team Collaboration each have a meaningful influence on Student Project Performance. The path coefficient for ChatGPT Integration → Student Project Performance ($\beta = 0.223$; $t = 2.025$; $p = 0.039$) suggests that the effective use of ChatGPT contributes moderately to improving students' project outcomes through enhanced task execution and problem-solving efficiency. The relationship between Communication Patterns → Student Project Performance ($\beta = 0.434$; $t = 4.781$; $p = 0.000$) shows the strongest effect among the three, emphasizing that clear, frequent, and structured communication within teams plays a crucial role in achieving successful project results. Meanwhile, Team Collaboration → Student Project Performance ($\beta = 0.341$; $t = 4.150$; $p = 0.000$) also demonstrates a significant positive impact, highlighting that mutual support, shared responsibilities, and effective coordination among team members are essential factors driving performance success. Overall, the findings confirm that both social and technological factors—namely collaboration, communication, and ChatGPT usage—collectively enhance students' ability to deliver high-quality project outcomes.

Discussion

The findings from this study provide compelling evidence that the integration of ChatGPT, combined with effective team collaboration and structured communication patterns, significantly improves student project performance in software engineering education. The results demonstrate that ChatGPT integration has a positive and significant effect on student project performance, supporting prior studies that suggest generative AI tools enhance students' problem-solving efficiency, creativity, and project output quality [3], [7]. ChatGPT's strength lies in its ability to provide instant feedback, generate code snippets, and explain programming logic, thereby reducing cognitive load and accelerating project development. In a software engineering practicum, where students must design, implement, and test applications collaboratively, ChatGPT acts as a cognitive amplifier, assisting in debugging and idea refinement. This aligns with the concept of AI as a learning companion, emphasizing human–AI collaboration that augments, rather than replaces, learners' cognitive abilities. However, while the positive influence of ChatGPT is clear, the effect size remains moderate, suggesting that its impact on performance is indirectly strengthened through teamwork and communication, consistent with socio-technical systems theory, which holds that technology yields optimal results when embedded within supportive social structures.

Team collaboration shows a strong and significant influence on student project performance, aligning with the works of [2], [9], which assert that effective teamwork is a fundamental determinant of productivity and satisfaction. Collaboration enables task specialization, idea exchange, and collective problem-solving—key competencies in software development teams. Students who demonstrated strong collaboration in this study reported higher satisfaction and better project deliverables. ChatGPT indirectly facilitated this collaboration by serving as a shared informational resource, offering clarity in technical tasks and harmonizing team workflows. When one member faced a coding challenge, others could leverage ChatGPT's explanations to collectively address and resolve the issue, fostering more cohesive teamwork. This finding reinforces Collaborative Learning Theory [10], which posits that learning and performance improvement occur through social interaction and shared meaning-making. Within this collaborative ecosystem, ChatGPT functions as a mediating artifact that enables knowledge exchange, coordination, and collective growth.

Among all constructs, communication patterns emerged as the strongest predictor of project performance, emphasizing that communication quality and frequency play a pivotal role in determining project-based learning success. This result is consistent with Salas et al. (2015), who found that clarity and responsiveness in communication are vital for maintaining shared understanding in team environments. Teams with effective communication were better equipped to resolve problems swiftly, coordinate tasks efficiently, and maintain motivation. In this study, ChatGPT strengthened communication by serving as a neutral intermediary that helped students articulate ideas, summarize discussions, and bridge cognitive or linguistic gaps. This dynamic aligns with the Computer-Supported Collaborative Learning (CSCL) framework [14], which argues that technology enhances knowledge co-construction by supporting structured dialogue and reflection. ChatGPT's capacity to clarify communication fosters shared understanding (common ground)—a crucial factor for success in software engineering projects that demand high levels of coordination and cross-functional expertise.

Overall, the findings highlight that the combination of human collaboration and AI assistance yields superior learning outcomes, supporting the emerging concept of AI-augmented education, where artificial intelligence serves as a facilitator rather than a replacement for human capability [20]. The mediating role of team collaboration—demonstrated through the indirect effect of ChatGPT on project performance—shows that the greatest educational value of AI emerges when learners actively engage with both the tool and their peers. ChatGPT provides cognitive scaffolding, while human interaction transforms this support into actionable insights and shared understanding. This outcome reinforces the Technology Acceptance Model (TAM) [23], which proposes that perceived usefulness and ease of use drive technology adoption. Students who viewed ChatGPT as an intuitive and beneficial learning aid integrated it effectively into their collaborative routines. The combined application of TAM and Collaborative Learning Theory thus offers a comprehensive framework for understanding how technological and social factors synergize to enhance learning experiences and improve student performance in technology-driven education.

Implications for Software Engineering Education

The findings carry significant pedagogical implications for software engineering education. First, curriculum design should formally integrate generative AI tools such as ChatGPT into coursework, allowing students to use them ethically and effectively through structured assignments like AI-assisted debugging, documentation generation, or requirement analysis to enhance both technical and soft skills. Second, collaborative learning frameworks need to be strengthened, as ChatGPT's effectiveness depends heavily on team dynamics; thus, instructors should design group-based projects that promote dialogue, peer mentoring, and shared responsibility while positioning AI as a supportive tool rather than a replacement. Third, digital literacy and ethics must be prioritized since ChatGPT can produce both accurate and misleading content; therefore, universities should develop students' critical evaluation abilities to ensure they can analyze AI-generated information responsibly. Lastly, assessment and evaluation systems should evolve to measure not only technical outputs but also the quality of collaboration and communication, ensuring a more holistic evaluation of student performance within AI-augmented learning environments.

Theoretical Contributions

The study contributes to the body of knowledge by empirically validating a socio-technical learning model in which human and artificial intelligences collaboratively create educational value. It advances three key theoretical insights: first, the extension of the Technology Acceptance Model (TAM), as the results confirm that the perceived usefulness of ChatGPT leads to higher collaborative engagement and improved learning outcomes; second, the support for Collaborative Learning Theory, showing that learning effectiveness increases through structured interaction facilitated by AI mediation; and third, the integration with the Computer-Supported Collaborative Learning (CSCL) framework, where ChatGPT strengthens digital collaboration by enhancing communication clarity and responsiveness within teams. Collectively, these insights demonstrate that ChatGPT integration enriches both the cognitive and social dimensions of learning, reaffirming the crucial role of technological mediation in shaping effective and interactive education in the modern era.

Limitations and Directions for Future Research

Although the findings are promising, this study has certain limitations. The sample was limited to one private university, which may restrict the generalizability of the results across other institutions or academic disciplines. To enhance future research, several directions are suggested: incorporating additional mediating variables such as digital literacy, creativity, or learning motivation to provide a more comprehensive model; comparing ChatGPT's impact across various academic programs such as business, design, or data science to capture disciplinary differences; conducting longitudinal studies to observe the long-term evolution of AI-assisted collaboration over multiple semesters; and integrating qualitative methods such as focus groups or interviews to gain deeper insights into students' experiences and perceptions of AI integration in collaborative learning environments.

CONCLUSION

The purpose of this study was to explore how the integration of ChatGPT influences student project performance through the mediating effects of team collaboration and communication patterns in software engineering education. The findings provide empirical evidence that effective use of ChatGPT enhances both the social and technical dimensions of learning, resulting in improved project outcomes. ChatGPT integration positively impacts student performance by supporting cognitive processes such as code generation, debugging, and problem-solving, allowing students to work more efficiently and manage their projects more effectively. Moreover, team collaboration serves as a vital mediating mechanism between ChatGPT use and performance, reaffirming that teamwork is the key channel through which technological tools create meaningful learning experiences. Collaboration fosters trust, shared understanding, and mutual accountability—elements that are amplified by ChatGPT's ability to provide consistent guidance and information. In addition, communication patterns emerged as the strongest determinant of project performance, as teams that maintained clear, open, and frequent communication achieved higher-quality results. ChatGPT supported these communication processes by helping students articulate ideas, clarify misunderstandings, and maintain consistent documentation, thereby reinforcing both the cognitive and relational dimensions of teamwork.

The structural model demonstrated a high explanatory power ($R^2 = 0.790$) and predictive relevance ($Q^2 = 0.785$), confirming that the proposed framework accurately captures the dynamics of AI-assisted collaboration in education. These results align with the Technology Acceptance Model (TAM) and Collaborative Learning Theory, highlighting that perceived usefulness and social interaction jointly determine learning effectiveness in AI-enhanced environments. From a practical perspective, this study emphasizes the need for educators to design AI-integrated learning frameworks that merge technological tools with collaborative pedagogical strategies. Instructors should encourage ethical, critical, and purposeful use of ChatGPT to enhance teamwork and communication rather than create dependency. Furthermore, institutions are advised to develop AI literacy programs that equip students with the skills and awareness necessary to navigate the evolving landscape of human–AI collaboration. In conclusion, the integration of ChatGPT in software engineering education provides significant benefits when combined with strong collaborative and communicative practices. Rather than diminishing human interaction, ChatGPT enhances it, serving as a co-creative partner that enables higher engagement, efficiency, and excellence in project outcomes. This synergy between artificial intelligence and human collaboration represents a transformative step toward the future of technology-driven education in Indonesia and beyond.

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