Investigating the Effectiveness of AI-Powered Collaborative Tools on Facilitating Group Projects in Higher Education Institutions

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ABSTRACT

The purpose of this study is to analyze the effects that AI-integrated tools have on collaborative learning outcomes within higher education in Vietnam. Based on collaborative learning theory, it observes the impacts of AI platforms regarding student engagement, communication efficiency, and perceived learning outcomes in group projects. 86 undergraduate students from three universities participated in a quasi-experimental between-groups design. The experimental group used some AI-supported platforms (e.g., ChatGPT, Notion AI, Google Docs AI), while the control group used traditional means (i.e., email, face-to-face meetings, standard Google Docs). The project lasted six weeks; both groups performed under exactly the same tasks and assessment criteria with corresponding deadlines. A mixed-method approach was adopted for data collection. Quantitative data were collected by a post-project survey analyzed with Statistical Tests plus some quality insight from semi-structured interviews involving 12 students and 4 instructors. Results indicate that the treatment group displayed significantly higher levels of engagement and communication effectiveness. Qualitative data further underscores improved management of brainstorming and reduced work pressure. It, therefore, brings to the limelight the potentiality of AI tools in managing cognitive and behavioral challenges within a collaborative setup. This information can be useful for developing technologically enhanced teaching methods in blended and online learning environments.

Keywords: AI-integrated tools, collaborative learning outcomes, group projects

Introduction

The quick mixing of artificial intelligence (AI) tech into higher education is changing how students learn, talk, and work together both worldwide and in Vietnam's growing academic scene (Luckin, 2018; Zawacki-Richter et al., 2019). As AI tools become more and more used in university classes, there is rising interest in knowing their teaching worth, mainly when it comes to student-focused learning methods.

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An area of growing relevance is collaborative learning, which involves more peer-to-peer engagement and has long been the seat of better academic outcomes, improved communication skills, and better teamwork abilities. Though the potential of AI in supporting learning is well documented, specific ways through which it intervenes in group dynamics and collaborations among undergraduates are less discussed, particularly outside the Western context in educational settings like Vietnam.

There has been a growing trend of utilizing group projects in undergraduate curricula across Vietnam, thus making it very appropriate and necessary to understand how AI-powered tools could improve or detract from students' collaboration efforts. This study will focus on what is herein termed AI-powered collaborative tools, broadly defined as educational technologies integrating the functionalities of artificial intelligence to facilitate group coordination, participation, and learning. Such tools may have potential in supporting fairer and more efficient teamwork, but the real impact they have on learners in university settings in Vietnam is not known.

This study fills the gap by exploring the impacts of AI-enabled collaboration tools on three major outcomes of undergraduate group projects: student engagement, teamwork efficiency, and learning outcomes. Therefore, it is guided by the following research questions:

1. How does the use of AI-powered collaborative tools affect undergraduate engagement in group projects in Vietnamese higher education?

2. How do AI-powered collaboration tools change the efficiency of groupwork for Vietnamese undergraduate project teams?

3. How do AI-powered collaboration tools impact the learning outcomes of Vietnamese undergraduates in group project settings?

This study hopes to answer these questions so it can add real facts from the situation to the ongoing talk about putting AI into group learning. It also wants to share useful tips for teachers, schools, and rule-makers in Vietnam and other places.

Literature review

Collaborative learning has always been regarded as a very successful pedagogical approach by which knowledge construction, critical thinking, and interpersonal skills can actively be developed (Barkley et al., 2014; Dillenbourg, 1999; Johnson & Johnson, 2009; Slavin, 1995). Collaborative learning emerged from sociocultural and constructivist theoretical perspectives as a shared inquiry process that involves reciprocal help among learners. It perfectly matches the requirements of modern higher education (Garrison et al., 1999; Gillies, 2016; Zawacki-Ritchter et al., 2019). Several meta-analyses confirmed that enhanced academic achievement added to improved student motivation that maintains long-term retention.

Despite its advantages, collaborative learning also presents persistent challenges. Students frequently report issues such as social loafing, uneven participation, poor coordination, and communication breakdowns (Hadwin et al., 2011; Janssen et al., 2011; Malmberg et al., 2015; Oakley et al., 2004; Strijbos & Fischer, 2007). These difficulties may be amplified in culturally diverse classrooms, where differences in communication styles, expectations, and power distance influence group dynamics (Hofstede, 2001; Huang et al., 2020; Hew et al., 2023; Puliti, 2019; Laal & Ghodsi, 2012; Roseth et al., 2008). In Vietnam, traditional teacher-centered norms and indirect communication practices can further complicate peer collaboration unless pedagogically mediated.

Digital tools were increasingly used to break these barriers. Google Docs, Microsoft Teams, and Padlet allow real-time editing, asynchronous collaboration, and version tracking, which can further support transparency while coordinating (Hrastinski, 2009; McNeil et al., 2000; Nguyen-Anh et al., 2023; Williamson et al., 2021). However, other studies have also established that digital tools are inadequate for sustaining group engagement or facilitating equal role negotiation among members when the groups are large and loosely structured (Strijbos & Fischer, 2007).

AI-driven cooperative instruments are heralded as a potential paradigm shift. These do not remain within the framework of conventional digital environments but rather are intelligent functionalities that can encompass real-time analytics, dynamic feedback, role distribution algorithms, and process monitoring (Holmes et al., 2019; Luckin, 2018). Therefore, much more personalized and data-driven support is possible to strive for more balanced input and reduce the normal strains of collaboration (Chen et al.,2020; Lin & Chen, 2024).

AI-driven tools applied to group learning settings span smart project management applications (for instance, Trello joined with AI examination) up to thought-creation or co-writing platforms supported by AI (examples include Notion AI and GrammarlyGO), as well as chat aids giving auto help or dispute cues. These tools are not the same as separate AI applications such as ChatGPT since they do not naturally work together unless added to team tasks.

Communication, coordination, and shared accountability between student groups were improved, as noted by Slavin (1995), Slavin et al. (2003), and Stahl et al. (2006) in their study using an AI-enhanced collaborative platform. As noted by Chen et al. (2020) and Oakley et al. (2004), reduced intra-group conflict occurred because tasks were equally distributed due to the monitoring features of the system, which were perceived to be driven by AI and which are actually supported by AI. Hadwin et al. (2011) describe feedback and contribution tracking tools when perceived to be driven by AI as motivating better self-regulation as well as more consistent participation from group members. This approach creates a scenario in which AI tools may have a secondary effect on improving group engagement and learning outcomes by enhancing efficacy.

The Community of Inquiry (CoI) framework (Garrison et al., 1999) best defines the theoretical underpinnings of AI-facilitated group work by suggesting that a meaningful online learning experience requires an amalgamation of teaching presence, social presence, and cognitive presence. In that way, AI tools may be applied as systems: firstly, to support teaching presence with automated and facilitated attached tasks; secondly, to support social presence in the structured interaction of peers; and finally, to enhance cognitive presence through related prompting and feedback.

Self-Determination Theory (DT) (Deci & Ryan, 2000) is also instrumental in showing the way personalized AI feedback helps fulfill learners' psychological needs for autonomy, competence, and relatedness. Motivational mechanisms therein may therefore inspire students to willingly participate in group tasks and sustain collaboration challenges. DT thus articulates how individualized AI comments dynamically facilitate or thwart the satisfaction of learners' psycho-social needs for autonomy, competence, and relatedness.

However, there are significant issues. First, what scholars have earlier warned is coming to pass: that using too much AI will reduce human interaction, critical thinking, or the development of soft skills that are required in future jobs (Holmes et al., 2023; Selwyn, 2007; Williamson, 2021). Algorithmic bias ethics, data privacy ethics, and even the inequality of access to AI infrastructure in educational systems being developed are currently rigorously discussed (Binns et al., 2018; Crawford & Paglen, 2021; Eubanks, 2018; Noble, 2018). In such a context as Vietnam, where readiness with technology differs greatly among universities and training regarding faculty members varies considerably, these issues have to be addressed critically (Nguyen, 2011).

Despite all these challenges, the existing literature asserts the increasing relevance and potential of AI-powered collaborative tools in improving educational outcomes. However, upon a meticulous review, it is found that most studies were implemented in Western contexts with inadequate consideration of cultural, pedagogical, and institutional conditions that differentiate Southeast Asian education systems. There is still a dearth of literature on how such tools work in Vietnamese institutions, where student learning preferences and classroom structures may be different from those of the Global North (Nguyen-Anh et al., 2023; Pham et al., 2021).

AI collaboration tools do promise a very viable solution to the perennial problems associated with group work, but how effective they are and how they impact the Vietnamese context have not yet been adequately established. This paper will be a response to this gap in knowledge by assessing the influence of AI-supported platforms on student engagement, group coordination efficiency, and learning outcomes of undergraduates in project-based learning environments. In doing so, it attempts to provide evidence-based insights that inform educational practice as well as theory in AI-contextualized collaborative learning.

Research Questions

To fulfill this study, the survey was seeking to answer the following research questions:

1. To what extent does the use of AI-powered collaborative tools affect undergraduate engagement in group projects in Vietnamese higher education?
2. How does the use of AI-powered tools influence the efficiency of groupwork among Vietnamese undergraduate project teams?
3. How do artificial intelligence collaborative tools impinge on group project undergraduates' academic performance in Vietnamese universities?

Methods

Pedagogical Setting & Participants

The research took place in six whole undergrad classes — three going to the experimental side and three to the control side at three schools in Vietnam. All students who signed up (N = 86; 62 females, 24 males; M age = 20.3 years old, SD = 1.1) participated in the number part, which was selected by an easy group choice method. This method was used to maintain the integrity of the normal class groups for both sides and is straightforward and easy to implement.

Maximum variation and purposive sampling were used to collect different perspectives as part of the qualitative strand. Twelve students—six per group, balanced by gender and academic major—and four instructors from those institutions who participated were selected for semi-structured interviews based on varying experiences with group dynamics and usability of the tool.

For the qualitative strand, maximum-variation purposive sampling was used to obtain different points of view. 12 students (6 from each group by gender and academic major balance) and 4 instructors (one from each participating institution) were selected for semi-structured interviews on the basis of different experiences with group dynamics and usability of the tool. The collaborative project ran for six weeks, being standard across all classes regarding topic, task complexity, deadlines, and assessment criteria. The students worked in groups of 4-5 to write a group report and deliver an oral presentation on a theme related to their course. Standardizing the procedure, facilitation was also guided by a manual that clearly stated expectations about support for students and assessment practices.

Design of the Study

The study used a quasi-experimental between-groups design, which is very handy since random assignment cannot always be actualized in real-world educational settings. Hence, comparison will be made between the experimental group that uses AI-integrated collaborative platforms and the control group that uses traditional collaboration methods without demolishing the existing classroom structures. The quasi-experimental approach fits best due to institutional constraints on random allocation in university classes and the fact that ecological validity must be maintained.

A group project over six weeks served as the intervention, which was implemented in all classes. The experimental group used ChatGPT, Notion AI, Google Docs AI, and Trello AI Assistant; this group is referred to as the AI-enhanced tools group. The other corresponding group is known as the control group and used email and face-to-face meetings plus standard Google Docs to carry out their tasks.

A mixed-methods approach allowed methodological triangulation, thus ensuring a wider perspective on the effects of the intervention. Quantitative data was obtained from post-project surveys implemented at the end of a six-week group project by both experimental and control groups. These perceptions cover engagement, communication efficiency, and learning outcomes. Qualitative data was used primarily as a complement to flesh out and better understand the quantitative results obtained above. Sources of such qualitative information were semi-structured interviews conducted with selected participants and open-ended survey responses that threw light on the reflections of students and educators on collaborative learning experiences in terms of group dynamics, usability of tools, and benefits and challenges of AI-enhanced platforms.

Data collection & analysis

Procedure (Intervention)

All participants engaged in a collaborative group project as part of their course requirement. The project, lasting 6 weeks, was identical for all classes and required teams to produce a joint final report and presentation on a course-related topic. At the onset of the project, we provided students in the experimental classes with access to an AI-powered collaboration platform that integrated a generative AI assistant. This tool (built on a large language model similar to ChatGPT) provided features such as real-time brainstorming support, automated summaries of team discussions, language enhancement suggestions, and intelligent task reminders. A brief training session was provided to the experimental group on how to use the AI features effectively and ethically (e.g., verifying AI-generated content, avoiding plagiarism). The control classes undertook the same project using traditional collaboration methods (e.g., email, standard discussion forums, and face-to-face meetings) without any AI assistance. Except for AI presence, everything else in the learning environment across groups was kept constant: same project instructions for students, same timeline, and same assessment criteria; instructors also facilitated all classes equally. Such an arrangement made it possible to attribute differences in results to the intervention. There was little direct instruction about collaboration during the six weeks; students managed their own team process. AI tool usage by the experimental group is logged automatically by the platform (frequency of AI-generated suggestions and how many queries are made to the AI), but there will be no corresponding logs for the control group other than normal communication records. Upon completion of the project, course instructors will evaluate all teams' deliverables on a common rubric, focusing on content quality, teamwork, and creativity. This project grade (percentage score) was taken as an objective measure of learning outcomes for each student (after normalizing with respect to individual contributions). Finally, a post-project survey and interviews (for a subset) of students were elicited as described below.

Data Collection and Instruments

It used a between-groups quasi-experimental design with a one-shot post-test. Random assignment of intact classes to treatments was not possible for logistical reasons, and because the design violated certain ethical canons, pre-testing could not be undertaken on practical grounds. Though no pre-test was administered in reality, this design permits meaningful comparison between groups after an intervention carefully controlled over six weeks.

Quantitative data was provided via a post-project survey that took place in the final week. The research team designed the instrument to measure three major outcome variables: student engagement, communication efficiency, and perceptions of learning outcomes. Multiple item measures were used for each construct, drawing on previous validated studies (Marks, 2000 for engagement; Kirschner, 2009 for communication; Alavi, 1994 for perceived learning). Demonstrated reliability and appropriateness to collaborative learning in higher education contexts informed the choice and adaptation of items.

Participants rated how much they agreed with each statement on a scale of 1 to 5, where one meant 'strongly disagree' and five meant 'strongly agree.' Example items are “I made an effort to participate in my team's talks for this work," "Our team shared thoughts and news well during the task," and "Doing this task helped me better know the course content."

Additionally, participants in the test group completed a brief AI feelings subscale consisting of four items. One sample item was "The AI tool helped us finish our task well." The survey had a question about past AI use to help make sense of the answers.

To further understand participant experience, particularly of AI tool usability and perceived effectiveness, qualitative components were also included, consisting of semi-structured interviews and open-ended survey responses related to objective 4.

A total of 30 students (approximately five from each class, with variation in academic performance and group roles) volunteered for post-project one-on-one interviews. Interview questions prompted reflection on group dynamics and AI use (where applicable), such as:

- *"How did the AI tool affect your engagement in the project?"*
- *"In what ways did it (or its absence) influence your team's communication and output?"*

Instructors (n = 10) were also interviewed about their observations of group functioning and collaboration quality. Additionally, all survey respondents were invited to respond to an open-ended item: "Please describe any ways in which the AI tool (or lack of it) affected your group work experience." These open responses supplemented the interview data, providing broader insight.

All interviews were conducted in either English or Vietnamese, depending on participant preference. Interviews were then transcribed and translated into English for thematic analysis.

Data Analysis

Quantitative Analysis

Survey responses were first coded so that higher values indicated more positive outcomes. Composite scores for engagement, communication efficiency, and perceived learning outcomes were computed by averaging the relevant Likert-scale items (after first checking for the one-dimensionality of each scale). Furthermore, students' actual project grades (in percentage) were collected as evaluated by the instructors.

Assumptions precede hypothesis testing: Independent samples t-tests were performed on the outcomes between the experimental and control groups (AI-supported vs. non-AI) for each key outcome variable, assuming a normal distribution of scores and equal variances as per Levene's test. Since these are measured on interval scales and since groups are independent, this type of analysis is appropriate. The significance level that has been adopted is $\alpha = .05$ (two-tailed).

A one-way ANOVA to assess possible effects at the class level across six classes was implemented. Since nothing significant turned up except the AI condition effect, it was decided to pool the data by condition. For each comparison made, group means and standard deviations, besides the t-value with degrees of freedom and p-value, have been reported. Effect sizes will also be provided as an indication of how large any differences between groups are. We ran a chi-square test of independence for the communication efficiency question (yes/no answer) to see if the share of people who agreed was different by group. Since we were looking at categories, it made sense to use chi-square as our test (Shadish et al., 2002).

Qualitative Analysis

Qualitative information, which includes open-ended survey responses and interview transcripts from 25 students, has been thematically analyzed using the six-step process outlined by Braun & Clarke (2006). The coding frame was inductively developed. Two trained researchers individually examined all student responses for recurring patterning. Text segments were initially coded with such labels as "more engaged due to AI" and "learning new skills." The coders then met to further discuss discrepancies in coding, refine the codes, and group related codes into higher-order themes.

Themes were developed in an iterative manner to best respond to the two major foci: (1) how they sit with the pre-set outcomes of engagement, communication, and learning, and (2) what students consider when using AI tools. For credibility purposes, an audit trail of all coding decisions was kept together, with some members checking the interpretation of themes carried out by a few respondents.

Findings and discussion

Student Engagement

Table 1.

Student engagement (participation) by condition: mean contributions and engagement scores for experimental vs. control groups.

Engagement Measure	Experimental Group (n≈90)	Control Group (n≈90)	*t* (df)	*p*	Effect Size (*d*)
Contributions per student (count)	15.3 (4.2)	10.8 (3.5)	$t(170)=7.10$	< .001**	1.02 (large)
Engagement survey score (1-5)	4.31 (0.54)	3.89 (0.60)	$t(178)=4.78$	< .001**	0.75 (moderate)

It was found that the use of an AI-powered tool significantly enhances group work engagement, since students from the experimental group showed evidently more active participation compared to those of the control group. This can be seen through self-reported engagement scores and objective behavioral data—two indicators of engagement.

From the post-project survey, it was observed that the mean engagement score of the composite participation-related Likert-scale items belonging to the experimental group on a 5-point scale was higher than that of the control group. The actual mean scores were 4.31 with a standard deviation of 0.54 for the experimental group and 3.89 with a standard deviation of 0.60 for the control group. This difference turned out to be statistically significant at $p < .001$ as calculated by $t(178) = 4.78$, giving an effect size that may be described as moderate at $d = 0.75$.

In the platform activity logs, it can be seen that students of the experimental group have contributed significantly more ($M = 15.3$, $SD = 4.2$) as compared to the control group ($M = 10.8$, $SD = 3.5$), $t(170) = 7.10$, $p < .001$, $d = 1.02$, which is a large effect. These two measures, self-reported engagement and contributions per student, complement each other in measuring overall engagement.

For a further qualification of these results, qualitative findings were pursued. Thematized responses from the open-ended questions and student interviews illustrated how the AI tool increased engagement and why it was effective. Major themes included novelty perceived plus motivation: students sensed that the AI assistant would provoke novel ideas, thereby making group work more lively. “The AI assistant kept our group on track by suggesting topics and asking questions—it made me want to contribute more so we could see what it would do next.”

Team identity plus support: Students noted that the AI was just 'an extra team member,' thus increasing their sense of collaboration and motivation. When there is no support, students struggle. As against this, the students of the control group said that they have lost interest, and it is very difficult to keep interested without any guidance.

Such qualitative themes further buttress the quantitative evidence, to the effect that the AI tool has raised students’ intrinsic motivation and made group experiences more structured and interactive.

The data above, when combined with some reflective feedback, indicate that the AI tool may be supporting both intrinsic and extrinsic forms of engagement. While raising visible contributions from students, it uplifts their feelings of belongingness and responsibility in group work. Such findings go a long way in support of Vygotsky’s sociocultural theory (1978) on the importance that mediated tools assume in collaborative learning settings. However, caution must be noted since a few students have indicated an increasing reliance on suggestions generated by AI.

Communication Efficiency

Table 2.

Perceived communication efficiency: categorical agreement and continuous scores.

Communication Efficiency Measure	Experimental Group (n≈90)	Control Group (n≈90)	t/χ^2	*p*	Effect Size (*d*)
Agreement Rate (%)	85%	60%	$\chi^2(1, N=180)=15.0$	< .001	-
Mean Likert Score	4.45 (0.50)	4.10 (0.58)	$t(178)=4.32$	< .001	0.66 (moderate)

Experimental group students reported much greater communication efficiency during group collaboration than control group students. As shown in Table 2, the data is of two types: 1. Categorical Agreement Rates: 85% of students in the experimental group who agreed or strongly agreed that “the AI-powered tool enhanced our team’s communication efficiency” compared to just 60% of students in the control group. A chi-square test of independence confirmed that this difference was statistically significant, $\chi^2(1, N = 180) = 15.0$, $p < .001$.

2. Mean Likert Score: The experimental group presented a mean score of 4.45 (SD = 0.50), while the control group presented a mean score of 4.10 (SD = 0.58). $t(178) = 4.32$, $p < .001$, $d = 0.66$ This comes out to a moderate effect size, and the results are statistically significant.

A thematic analysis of the open-ended responses to the survey and interviews conducted helped understand the mechanisms that lay beneath these perceptions. Three major themes were discussed:

- Streamlined coordination: Fewer cases of miscommunication and easy task allocations were reported by students belonging to the experimental group. As shared by one of the students, "The AI would suggest meeting agendas and even draft messages, which made our interactions more structured and to-the-point."
- Made things clear and put in: Students called the AI a talk helper. It cleared up points that were not clear, summed up ideas from the group, and helped non-native English speakers to make their thoughts clearer.
- Cut down on time spent getting things in order: Many said that the AI cut down on time for admin or setup work so the group could spend more time on the main task. As one student put it, "Instead of arguing about who would write which part, the AI helped assign and remind us that it made things smoother."

Control group students reported normal coordination problems like scheduling conflicts, late replies, and unclear who should do what: "Sometimes, no one replied for hours, and we didn't know what was happening," said one participant. This, therefore, means that the tool helped them by giving structured prompts, helping with clarification support, and providing just-in-time feedback. Quantitative evidence of statistically significant differences in both categorical and continuous measures, plus qualitative themes of clarity and coordination and reduced overhead, strongly converges to embed the conclusion that intervention by AI improved students' perceptions of group communication.

On a theoretical note, results fall in line with what Cognitive Load Theory proposed. If the extraneous load in planning, clarification, and logistics is reduced by AI, students would have more cognitive resources left to be allocated towards the actual task of the project. Therefore, this gives a better scaffolding effect when implemented in group work since group work always contains a lot of vagueness and miscommunication that militates against progress.

A few students expressed caution about over-reliance, noting that they had in fact adopted suggestions from the AI without checking their relevance. This raised an ethical concern for some of them, who questioned whether it was fair to use AI to assist in managing collaboration. Transparent guidelines and pedagogical framing are thus highlighted by these perspectives as an imperative when integrating AI into collaborative learning contexts.

Learning Outcomes

Table 3.

Final project performance by condition: mean project grade for experimental vs. control groups.

Learning Outcome Measure	Experimental Group (n=85)	Control Group (n=93)	*t* (df)	*p*	Effect Size (*d*)
Project grade (% score)	82.5% (5.0)	78.0% (6.3)	*t*(176)=4.02	< .001**	0.78 (moderate)

Table 3 shows that the average grade of projects for the experimental group came out to M = 82.5%, SD = 5.0, much higher than for the control group at M = 78.0%, SD = 6.3. The results of an independent samples t-test between these two groups yielded $t(176) = 4.02$, $p < .001$ with a moderate effect size of $d = .78$. This is a mean difference of 4.5 percentage points on actual academic performance attributable to using the AI-assisted collaboration environment—a real difference in objective academic achievement that could be translated into letter grades by all instructors evaluating projects under standardized rubric criteria for accuracy, clarity, and teamwork while being completely unaware of group conditions.

To better understand how AI support influenced project performance, we analyzed qualitative data from student reflections and instructor feedback. The analysis identified three major themes:

- Efficiency and idea generation: Students from the experimental group indicated that the AI tool enabled them to quickly gather content and organize some, thereby providing more time for higher-order thinking. One participant shared, "The AI helped us gather information quickly, and therefore we can generate ideas for our report. This means we could spend more time refining content rather than scrambling for basics."
- Scaffolding and troubleshooting: The AI was meant to be perceived as a secondary facilitator. Learners detailed how the AI would give solutions or pointers once their group discussion reached a dead end. "Whenever we got stuck, we asked the AI for suggestions. Even if we didn't always use them, it sparked new approaches," noted another learner. Meanwhile, those in the control group shared sentiments of agony: "We had to do all the research and troubleshooting ourselves, which took a lot of time."
- Instructor observations: According to all, the presentations by some groups using AI appeared more polished and coherent. "In fact," noted one of the instructors, "some of the AI-group presentations were very deep and at the same time so well-organized." But here too, a few teams' content was overused and not integrated well.

Results of this study, therefore, assert that the AI-powered collaborative tool uplifts and upgrades students' learning experiences in three interwoven dimensions: engagement, communication efficiency, and project performance. This improvement has been very well captured quantitatively (participation metrics going up and scores on projects being better) and qualitatively as well to prove the effectiveness of the intervention not just at a surface level but deep inside with pedagogical meaning attached to it.

Increased motivation and more active participation throughout the process of the group project were reported by students. Quantitative engagement scores improved as indicated by log data showing more evenly distributed contributions across team members. These results are perfectly consistent with what SDT assumes: meaningful learner engagement as a function of support for their needs related to autonomy and competence (Ryan & Deci, 2000). The AI tool seemed to be perceived as facilitating whereby it prompts contribution rather than dictates content, thus triggering ownership feelings together with collaborative responsibility that are consistent with what Reeve (2012) described and Shin et al. (2023) found.

Analysis indicated that the AI application enhanced communication efficiency. Such features as message summarization, task suggestions, and grammar checking minimized logistical misunderstandings within the platform. This data confirms previous studies that found results showing reduced extraneous cognitive load since support for low-level tasks is made possible by AI, thus enabling learners to focus more on the development of ideas through group negotiation (Holmes et al., 2019; Huang et al., 2023). Particularly, more optimistic support for real-time linguistic support expressing ideas from non-native English speakers was reported in previous studies by Javed et al. (2023) and Lin and Chen (2024); hence, similar findings regarding the inclusiveness potential of AI in group learning environments.

This study found that the AI-powered collaborative tool improved students' experience of three interlocked dimensions: increased engagement, heightened communication efficiency, and improved project performance. It is supported by quantitative data from metrics of increased participation and higher project scores as well as qualitative responses. This was not only an effective intervention but also a meaningful one in terms of pedagogy.

Student motivation increased with much keener involvement at every stage of the group project process. Quantitative engagement scores improved, but log data indicated contribution was much more evenly distributed across all team members.

It is explainable by the SDT motivation theory, which postulates that meaningful engagement is better elicited when there is support for the autonomy and competence of learners in learning contexts, not in any context outside learning (Ryan & Deci, 2000). In this case, the AI tool apparently assumes a role as an initiator rather than making content prescriptive, thus enabling the taking-on of collaborative responsibility described by Reeve (2012) and Shin et al. (2023).

It also assisted in boosting communication efficiency. Students also mentioned smart message summarization and grammar correction, which helped chop off sources of miscommunication and made some parts of logistical coordination better between teams who speak differently. This finding aligns with earlier literature on how AI reduces extraneous cognitive load by performing low-level tasks so that learners can concentrate more on idea development and negotiation among a group (Holmes et al., 2019; Huang et al., 2023). Specifically, real-time linguistic scaffolding support made non-native English speakers feel confident in expressing their ideas. This is consistent with the findings of Javed et al. (2023) and Lin and Chen (2024) regarding the inclusive potential of AI in group learning environments.

Conclusion

This study will add to the increasing literature on the pedagogical affordances and challenges of integrating AI-powered tools in higher education. Through a mixed-methods design, this paper has found that AI-supported collaboration yields higher student engagement, better communication efficiency, and improved group project performance. Most importantly, these findings have not only come out in terms of numeric outputs but have also been qualitatively reflected by the students and instructors involved, thus indicating a convergence of perception toward the positive role of AIs in structuring group processes and participation support.

The gains of AI integration do not come without trade-offs. Results showed that while AI would work to the enhancement of collaborative learning experiences, it could also introduce newer risks—reduced interpersonal interaction, over-dependence, and ethical ambiguity. These underscore the role that human oversight - in terms of pedagogical intentionality - plays. In this regard, AI is not seen as a replacer of human collaboration but rather complements it and needs an implementation process to preserve and promote very essential academic skills.

Essentially, this study brings to the fore the two-fold character of AI in education: on the one hand, it holds out great hope for facilitating group work and enhancing learning processes; on the other hand, it will only be as valuable as the pedagogical ecosystems into which it is absorbed that prioritize equity and responsibility and student agency. The nuanced and critically reflective approach will be key to ensuring that the integration of AI tools enhances - not undermines - the core purposes of higher education.

A multi-pronged approach that maximizes access benefits and effectively mitigates attendant challenges should, for best practice, include educator training, student access support, and continuous research-informed policy development. Therefore, these institutions must implement a comprehensive strategy that includes training educators through practical workshops on new AI tools to address the steep learning curve; ensuring educators understand the functionalities of the platforms and pedagogical strategies for blending AI with traditional collaborative learning methods; developing an understanding of ethics to teach students how to use AI responsibly while balancing intelligence assistance with human effort; and finally, raising awareness about issues such as algorithmic bias and data privacy.

Access should be wide and strongly supported for all students, not just those who know much about tech or have a certain background. This means picking or making platforms that are easy to use and putting them right into the LMS (learning management systems) already there so no extra steps get in the way. Furthermore, tech help and special lessons on AI rules must be there to help students work these tools well and in the right way. At last, new facts and changeable rules are key when dealing with the always-shifting world of AI in teaching. Long looks should be pushed to better see the profound effects of group work helped by AI on student interest, teamwork patterns, and learning results over time. These checks can also spot any new moral or private concerns that might arise from long AI use and steer needed safety steps. They can also detect any emerging ethical or personal issues that could come up in the long run with the use of AI and guide the necessary protective actions. The results of such reviews should be institutionalized into new policies guiding the application of AI tools to ensure that such frameworks are aligned with both the ethical standards and educational objectives of encouraging students to explicitly and consciously think critically without sliding into a dependency syndrome on any type of help, including AI. This will be achieved through comprehensive educator preparation plus student support and inclusive evidence-based policy frameworks towards promoting an effective as well as responsible integration of AI-powered collaborative tools in group projects in higher education and consequently improving learning experiences and outcomes.

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