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Human-Machine Interaction in Collaborative Learning Projects New Models of Role Distribution between Students and AI

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DECLARATIONS

Ethical Statement:

This research was conducted in accordance with the COPE Core Practices and principles of academic integrity, transparency, and responsible research.

Data Availability Statement:

Data supporting this study are available from the corresponding author upon reasonable request, where applicable.

AI Declaration:

The authors acknowledge the use of AI tools in conducting and preparing this research and remain fully responsible for its content, accuracy, and originality.

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Abstract

Artificial intelligence increasingly works alongside students within collaborative learning projects, raising fresh questions about role distribution. Classrooms once assumed only human members held decision-making responsibility, yet generative tools now shape planning, drafting, and problem-solving directly. This gap forms the background for this study. The research aimed to examine current role patterns, develop a structured distribution model, and assess how clarity affects fairness, accountability, and learning outcomes between students and artificial intelligence. A qualitative, doctrinal approach guided the study, relying on document analysis of scholarly literature and applicable regulatory frameworks. Results show that students and artificial intelligence divide tasks along predictable lines, with drafting shifting toward AI while judgment remains largely human. Clear roles strengthened accountability, fairness perceptions, and learning outcomes across collaborative teams. The study recommends structured disclosure practices and reflective AI use within classroom policy. These findings support building fairer, transparent collaborative learning environments for future educational technology governance.

Keywords: Human-Machine Interaction, Collaborative Learning, Role Distribution, Artificial Intelligence, Academic Accountability, Fairness Perception, Educational Technology Governance

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I. INTRODUCTION

Can a machine truly share responsibility in a student project today? Classrooms once separated human effort from digital tools completely. Today, artificial intelligence works beside students inside group projects and shared tasks. This shift changes how learners plan, discuss, and divide collaborative work. Human-machine interaction now shapes who leads a task and who assists. Students negotiate roles not only with peers but also with intelligent systems. These systems suggest ideas, correct errors, and sometimes challenge student judgment during teamwork. This blending of human and machine contribution raises fresh questions about fairness. It also raises questions about authorship, accountability, and genuine learning outcomes. Traditional group work models assumed only human members held decision-making power. New models must explain how AI earns a functional role inside teams. This evolving relationship matters greatly for teachers designing group assignments today. It also matters for policymakers shaping guidelines for responsible classroom technology use (Cukurova, 2026).

Collaborative learning has long relied on peer discussion, shared planning, and mutual accountability. Group projects taught students how to negotiate ideas and manage disagreements together. Recent advances in artificial intelligence introduced many new tools into these group settings. Chabot's, writing assistants, and adaptive platforms now sit inside classroom workflows daily. Early studies treated these tools as simple aids for individual student tasks. Few researchers examined closely how such tools function within group dynamics directly. Educators began noticing that AI could take on organizing or drafting roles. This created situations where machines influenced group decisions rather than merely supporting them. Scholars have studied human-AI collaboration mostly in workplace or single-user contexts. Classroom group projects received comparatively less focused theoretical or empirical attention. This gap leaves teachers without clear frameworks for structuring AI-inclusive group work. As artificial intelligence tools grow more capable, this gap grows increasingly important to address soon (Chiu, 2025).

Many classrooms now let students use artificial intelligence during group assignments freely. Yet clear rules for dividing tasks between students and AI rarely exist. Teachers often simply assume that group roles apply only among human teammates. This assumption ignores how AI tools actively shape group decisions and outputs. Students often report confusion over which contributions belong to them versus their tool. Some students lean heavily on AI suggestions without discussing this within their group. Other students resist AI input, fearing it might reduce their own learning. This inconsistency creates unequal collaborative experiences across different student groups and teams. Existing role distribution models describe only human-to-human responsibilities within group projects. These models cannot explain how machine contributions fit into shared team accountability. This research addresses that missing structure by proposing new role distribution frameworks. These frameworks include both human students and artificial intelligence as functional collaborators today (Chiu et al., 2024).

Recent research offers early evidence about artificial intelligence within collaborative learning projects. One study examined how generative artificial intelligence applications contribute to group project outcomes. Researchers found that these applications directly influenced task planning and role assignment. Students using AI tools distributed tasks differently compared to fully human-led groups. AI often took on drafting, summarizing, or idea-generation functions within team workflows. This shifted human members toward evaluating, editing, and refining machine-generated contributions. The study noted that clear task boundaries improved project quality and satisfaction levels. Groups without defined boundaries experienced confusion over ownership and final accountability for their work. These findings suggest that role clarity matters more as AI involvement increases. Without structured guidance, students struggle to negotiate fair distribution of collaborative responsibilities among teammates. Teachers reviewing these outcomes gained early insight into emerging AI-supported group dynamics. Such insight helps future instructors plan clearer, fairer group assignment structures (Alkalbani, 2024).

Another study explored generative artificial intelligence integration within an introductory research methods course. Researchers observed transformed group work patterns after students gained access to AI tools. Students used artificial intelligence to organize literature, draft sections, and check accuracy. This changed traditional group roles, since fewer tasks needed strictly human execution alone. Some students became coordinators, managing what AI produced rather than producing content. This role shift required new skills, including prompt writing and critical output evaluation. The study found that groups adapted differently depending on prior technology experience levels. Students familiar with digital tools integrated AI more smoothly into shared responsibilities. Less experienced students needed additional guidance to avoid over-reliance on generated content. These findings highlight the need for structured training alongside AI-supported group projects. They also show why role clarity should guide future collaborative classroom design. This evidence supports building clearer role models for mixed student-AI teams (Bezcioğlu-Göktolga, 2025).

Existing literature offers useful insight into artificial intelligence within collaborative learning environments generally. Most studies focus narrowly on single tools or short-term classroom interventions. Few studies propose structured models for distributing roles between students and artificial intelligence. Research on mixed reality and cognitive-emotional interaction hints at deeper collaborative complexity. Yet these findings remain isolated from broader frameworks describing sustained human-machine teamwork roles. Current models rarely address how responsibility shifts as AI capability grows within projects. They also rarely explain how teachers should evaluate mixed human-AI collaborative contributions fairly. This gap limits practical guidance for designing group assignments involving artificial intelligence tools. This research proposes a new model addressing that identified gap systematically. It examines how role distribution evolves within human-machine collaborative learning project settings. Filling this gap gives teachers a tested

structure for future group assignments. It also gives researchers a foundation for studying mixed-agent teamwork (Dang et al., 2025).

To examine how students and artificial intelligence currently share roles within collaborative learning projects.

To develop a structured model for distributing tasks between student teams and AI tools.

To assess how role clarity affects fairness, accountability, and learning outcomes in group work.

How can collaborative learning projects distribute roles fairly and effectively between students and artificial intelligence tools?

Artificial intelligence use in classrooms continues expanding rapidly across many educational institutions. Guidance for structuring group work involving these tools remains limited and inconsistent. Teachers currently rely on informal judgment rather than tested collaborative role distribution models. This creates inconsistent experiences for students working across different classes and instructors. A tested model would give teachers reliable guidance for structuring group assignments. It would also give students consistent expectations regardless of which course they take. Without such guidance, unequal artificial intelligence use may unfairly advantage certain student groups. This research responds directly to that pressing and growing classroom challenge. Studying role emergence during self-regulated learning processes reveals how responsibilities shift. These dynamics support the case for structured, evidence-based role distribution frameworks in education. This justifies developing and testing a new model within real collaborative learning settings. Such testing benefits both current classrooms and future collaborative learning research (Chen et al., 2025).

II. METHODS & METHODOLOGY

This research follows a qualitative approach suited to legal and policy-based inquiry work. Qualitative methods allow careful, close examination of concepts, rules, and evolving classroom practices. Doctrinal analysis forms the core method, examining laws relevant to artificial intelligence in education. This includes data protection rules, academic integrity regulations, and generative artificial intelligence guidance. The population for this study consists of existing scholarly literature and current regulatory frameworks. Rather than surveying individuals directly, the research draws its sample from published academic and legal sources. This sample includes peer-reviewed journal articles, institutional policies, and official government publications. Selection focused specifically on materials relevant to human-machine interaction within collaborative learning contexts. This qualitative, doctrinal design fits research questions concerning role distribution and shared accountability well. It allows detailed interpretation of existing rules rather than simple statistical measurement of behavior. This approach supports building a structured model grounded firmly in literature and current regulation.

Data collection relied on structured keyword searches across major scholarly databases and legal repositories. Search terms included human-machine interaction, collaborative learning, role distribution, generative artificial intelligence, and governance. Additional keywords covered academic integrity, algorithmic accountability, and educational technology governance frameworks. These keywords helped locate both empirical studies and formal, relevant legal or policy documents. Scholarly articles were retrieved through established academic databases indexing peer-reviewed education and law journals. Legal and regulatory materials were retrieved directly from official government and university websites. Official portals provided verified, current versions of applicable laws and detailed educational policy guidance. This combination ensured that findings reflected both current academic knowledge and formal regulatory expectations. Materials unrelated to collaborative learning or artificial intelligence governance were excluded from the review. This targeted collection strategy supported building a focused, relevant evidence base for analysis. The resulting collection formed the foundation for the doctrinal and document-based analysis conducted next.

Validity and reliability were maintained by prioritizing recent scholarship and currently applicable legal provisions. Sources published within the last five years were prioritized wherever suitable material existed. Older laws were included only when they remained currently active, applicable, and legally binding. Data analysis relied on doctrinal analysis for legal material and document analysis for scholarly literature. This dual approach allowed systematic interpretation of both regulatory text and academic findings. Ethical considerations required using only official documents already available within the public domain. Every scholarly source used within this research received full and accurate reference citation. This practice credits original authors and maintains transparency throughout the entire research process. No personal or identifying information was collected, since no human participants were involved directly. Limitations include the fast-evolving nature of artificial intelligence technology and its related policy. Laws governing artificial intelligence may change quickly, affecting the long-term applicability of these specific findings.

III. RESULTS& FINDINGS

This section presents results on human-machine interaction within collaborative learning projects. It examines how students and artificial intelligence divide tasks during group work. The analysis draws directly on the research objectives and the central research question. That question asked how collaborative projects can distribute roles fairly and effectively. Findings below describe patterns across task delegation, accountability, fairness perceptions, and learning outcomes. Each result connects observed classroom behavior back to the proposed role distribution model. Log-based evidence from similar collaborative settings shows measurable markers of shifting group roles. These markers help explain when artificial intelligence moves from a supporting position. They also show when it becomes an active decision-making participant within teams. These shifts support the broader goal of building a clear distribution model. The results together answer how fair collaboration can

occur between humans and machines. They also clarify practical boundaries that teachers and students can apply directly (Jiang, 2025).

Results show that students and artificial intelligence now share tasks in emerging patterns. Students typically retain control over planning, decision-making, and final project evaluation. Artificial intelligence more often supports drafting, summarizing, and generating initial content ideas. This pattern answers the first research objective, which examined how roles currently divide. Groups reported that AI functioned as a partner rather than a simple tool. Human partners still valued their own judgment above machine-generated suggestions during discussions. This finding supports the research question about fair and effective role sharing. Fairness improved when students actively reviewed and revised artificial intelligence contributions together. Groups that ignored this step reported lower satisfaction with final project quality. These emerging patterns suggest early natural boundaries forming between human and machine work. Recognizing these patterns helps build the structured model this research aims to propose. This result confirms that clear division of labor improves collaborative learning experiences (Daryanto, 2026).

Results reveal specific task types students most often delegate to artificial intelligence tools. Students frequently assigned literature searching, drafting, and language editing tasks to AI. Complex reasoning, argument construction, and final judgment remained primarily human responsibilities within groups. This finding directly addresses the second objective, which sought a structured task model. Delegation patterns varied depending on project complexity and available group time constraints. Groups facing tight deadlines delegated more drafting work to artificial intelligence tools. Groups with more available time retained greater control over content generation themselves. This variation suggests that task delegation should remain flexible rather than fixed permanently. A structured model must therefore allow adjustable boundaries based on project circumstances. These results help answer the research question by identifying practical delegation boundaries. Clear task categories reduce confusion when teams decide who handles which responsibility. This structure supports fairer and more predictable collaboration between students and machines (Gong, 2024).

Results indicate that role clarity strongly influences accountability within mixed human-AI teams. Groups with clearly defined roles reported fewer disputes over project ownership and credit. Unclear boundaries between human and machine contributions created confusion about individual responsibility. This finding relates directly to the third research objective concerning fairness and accountability. Students working in clearer groups could explain exactly which tasks artificial intelligence completed. This transparency allowed instructors to assess individual student contributions more accurately and fairly. Groups without clear roles struggled to separate student effort from machine assistance. Such confusion sometimes led to unfair grading outcomes across different group members. These results answer the research question by linking clarity directly to fairness. Clear role assignment also improved trust between group members during collaborative tasks. Students reported feeling more confident when responsibilities were explicitly stated beforehand.

This result strengthens the argument for structured, transparent role distribution frameworks (Du et al., 2026).

Results show that student perceptions of fairness depend heavily on visible AI involvement. Students felt collaboration was fair when artificial intelligence contributions remained transparent and traceable. Hidden or unexplained AI assistance often triggered suspicion among other group members. This finding connects to the objective assessing fairness within mixed human-AI teams. Students preferred systems where artificial intelligence suggestions required explicit human review first. Groups following this practice reported higher trust and stronger collaborative relationships. Students without such review processes expressed concern about unequal effort across members. Some worried that heavy AI use reduced genuine learning for less engaged students. These concerns directly answer the research question about achieving fair role distribution. Fairness perceptions improved further when instructors clarified acceptable artificial intelligence use beforehand. This clarity reduced anxiety and supported more positive attitudes toward collaborative technology. These results confirm transparency measures matter for building fair mixed-team collaboration structures (Hao et al., 2025).

Results demonstrate that artificial intelligence involvement affects student learning outcomes in measurable ways. Moderate AI involvement supported deeper student engagement with course material and content. Excessive reliance on artificial intelligence reduced independent thinking and critical analysis skills. This finding addresses the third objective concerning learning outcomes within collaborative environments. Students who reviewed and questioned AI suggestions developed stronger self-directed learning behaviors. Passive acceptance of machine-generated content correlated with weaker retention of course concepts. These results answer the research question by showing balance matters more than exclusion. Complete avoidance of artificial intelligence tools did not necessarily improve learning outcomes. Instead, guided and reflective AI use produced the strongest educational benefits for students. This finding supports designing role distribution models that encourage active student engagement. Such models should require students to evaluate rather than simply accept AI output. This result confirms that thoughtful integration best serves genuine collaborative learning goals (Gürbüz, 2025).

IV. DISCUSSION & ANALYSES

The students and artificial intelligence share responsibility. Roles shift depending on task type and classroom context. This pattern carries real significance for how classrooms structure collaborative assignments going forward. When students understand emerging boundaries, they plan tasks with greater confidence and clarity. Teachers gain a practical reference point for guiding students toward balanced, fair collaboration. Recent learning design frameworks already stress structured support for student-AI collaborative activity. Such frameworks recommend defining artificial intelligence involvement before group work begins, not afterward. This proactive approach matches what these emerging role patterns suggest across classroom settings. Institutions adopting these principles report smoother

transitions when introducing generative tools into coursework. The pattern also signals a shift away from viewing artificial intelligence as optional support. Instead, it increasingly functions as an expected collaborator within modern group learning environments. Recognizing this shift early helps departments prepare relevant policy and instructional guidance (Kim, 2022).

Supporting evidence for this pattern comes from classroom activities built around structured self-determination principles. Groups following socially shared regulation frameworks showed more consistent role division among members. Students guided by such frameworks reported clearer expectations for artificial intelligence involvement throughout tasks. This structure reduced hesitation about when to rely on machine-generated suggestions during work. Mathematical modeling activities using generative tools revealed similar boundaries between human and machine input. Students retained ownership of reasoning steps while allowing artificial intelligence to support calculation and formatting. This division mirrors patterns observed across broader collaborative learning environments in this research. It suggests that structured regulation strategies help students negotiate roles more effectively together. Evidence also indicates that early guidance shapes how groups later use available AI tools. Groups receiving initial structure adapted their role distribution more smoothly during ongoing project work. This consistency across different subject areas strengthens confidence in the pattern (Kaya, 2026).

Additional evidence emerges from Chabot design research focused on strengthening collective group efficacy. Well-designed conversational tools encouraged students to discuss roles openly before assigning specific tasks. Groups using these tools reported stronger shared confidence in completing collaborative assignments successfully. This confidence appeared linked to clearer communication about which member handled which responsibility. Design choices within these tools shaped how naturally roles distributed themselves across each team. Tools prompting reflection before task completion produced clearer separation between human and machine contribution. This finding reinforces the earlier pattern showing boundaries emerging through structured, guided interaction. It further suggests that tool design itself influences how collaborative roles take shape. Thoughtful chatbot architecture, therefore, becomes relevant to broader questions about fair task distribution. These findings point toward design as a meaningful lever for shaping classroom collaboration patterns. Applying similar design principles elsewhere could help replicate these encouraging role distribution outcomes (Kim & Lim, 2025).

Some limitations affect how confidently these emerging patterns generalize across different educational settings. Much available research still relies on small groups studied within single university courses. Students in these studies often already had some prior exposure to digital collaboration tools. This familiarity may have influenced how naturally they negotiated roles with artificial intelligence. Software-focused studies mainly examined technical collaboration rather than broader legal or policy-driven coursework. Findings from programming contexts may not fully transfer to humanities or law-related group projects. Self-reported perceptions also introduce possible bias, since students may describe

collaboration more favorably. Observation-based data remains limited compared with the volume of self-reported classroom experiences. Short study durations further restrict what researchers can learn about role patterns across a full term. Researchers examining generative AI use during collaborative programming tasks noted similar reporting constraints. These limitations do not remove the pattern's relevance but do call for cautious interpretation (Kiesler, 2025).

Comparing these findings with related studies reveals both agreement and some notable contradictions. Several studies confirm that artificial intelligence increasingly takes on supportive, non-decision-making functions within teams. Yet some student perception research shows mixed reactions toward AI-assisted collaborative learning experiences. While many students welcomed AI support, others expressed discomfort sharing credit with a tool. This contradiction suggests that comfort with shifting roles varies across individual students significantly. Course subject, prior technology exposure, and instructor guidance all shape these differing reactions strongly. Institutional policy also influences comfort levels, since clearer rules reduce uncertainty about acceptable use. Recent university guidelines on generative artificial intelligence use show growing attention to this concern. Some institutions now require explicit disclosure of AI involvement within submitted group assignments. Such policies directly shape how students perceive fairness within their collaborative learning experience. These comparisons highlight that role distribution patterns remain sensitive to local classroom context (Kim, 2026).

Together, these findings carry practical value for designing clearer collaborative learning frameworks going forward. Institutions can use these patterns to draft guidance for structuring group assignments involving AI. Clear boundaries around artificial intelligence use appear to support fairer, more transparent collaboration. Teachers benefit from concrete examples showing how roles naturally distribute across successful group projects. Students benefit from reduced confusion when expectations around AI involvement are stated clearly beforehand. Hybrid intelligence research supports pairing human judgment with machine assistance under thoughtful, structured conditions. This applicability extends beyond individual classrooms toward broader institutional technology policy development efforts. Universities updating academic integrity guidelines can draw directly on these observed role patterns. Policymakers shaping national education technology strategies may also find these patterns practically useful. As generative tools continue spreading across classrooms, structured role guidance becomes increasingly necessary everywhere. These findings offer a foundation for ongoing policy and classroom development work (Kong, 2025).

This tasks students most often hand to artificial intelligence. Drafting, literature searching, and language editing emerged as the most delegated activities. Complex reasoning and final judgment remained largely within human control across groups. This distinction matters greatly for designing fair and workable collaborative assignment structures. When teachers know which tasks shift toward AI, they can plan grading more accurately. Students also benefit from clearer expectations about which contributions require independent thinking. Recent scholarship describes this shift as part of a broader transformation in ed-

ucation. Human intelligence and artificial intelligence now combine within many classroom tasks simultaneously. This combination changes how instructors define original student work within group projects. Recognizing exactly where delegation happens helps prevent unclear or unfair grading practices. It also supports departments updating assignment guidelines to reflect current classroom technology use. These insights give practical direction for institutions building clearer collaborative task frameworks (Li, 2026).

Supporting evidence comes from research tracking how generative artificial intelligence use has evolved recently. Earlier classroom studies mostly discussed AI as a general writing or research aid. Newer studies map specific task categories where students consistently choose artificial intelligence support. Literature searching and initial drafting appear repeatedly across many different classroom project types. Editing and formatting tasks also shifted quickly toward artificial intelligence once tools became accessible. This evolving pattern shows students adapting delegation choices as tool capabilities keep expanding further. Groups increasingly treat certain tasks as routine, assigning them to AI without much discussion. Other tasks, especially argument building, still require deliberate human negotiation within the group. This split suggests a stable core of tasks resistant to full automation currently. Tracking these shifts over time helps researchers predict where future delegation boundaries may move. Such tracking also supports timely updates to classroom guidance as tools continue changing (Kumar, 2026).

Further evidence comes from flipped learning environments where artificial intelligence supports independent student preparation. Students in these settings often delegate background research and organizing tasks to AI. Face-to-face group time then focused more on discussion, argument, and shared decision-making. This redefined division allowed students to spend classroom time on higher-value collaborative work. Roles shifted so that artificial intelligence handled preparation while students handled interpretation and debate. This pattern closely matches the broader task delegation results found across other classroom settings. It also shows how course design choices can shape which tasks students delegate. Flipped formats appear especially suited to structured task division between students and AI tools. Institutions experimenting with flipped models report smoother integration of generative tools into coursework. This evidence strengthens confidence that task delegation follows predictable, structure-dependent classroom patterns quite generally speaking. Redefining roles this way also prepares students for future mixed human-AI work settings (López-Villanueva, 2024).

Some limitations shape how confidently these task delegation patterns apply across different educational contexts. Many studies focus on short courses rather than full academic programs over time. Students in these courses may not represent broader populations with varied technology access. Lifelong learning research suggests delegation habits may shift again as learners gain more experience. Group work patterns observed early in a course often differ from later patterns. This change makes single-point measurements less reliable for describing long-term delegation behavior accurately. Self-reported task categories also depend on how honestly students describe their own AI use. Some students may underre-

port heavy reliance on artificial intelligence for sensitive academic tasks. Institutional context, including available tools and internet access, further limits comparison across different settings. These factors suggest results should guide, rather than fully predict, delegation behavior everywhere. Continued longitudinal study would help clarify how stable these observed delegation patterns truly remain (Mozelius, 2025).

Comparing these findings against legal and governance research reveals additional considerations worth noting here. Legal scholarship on algorithmic decision-making stresses accountability whenever automated systems influence outcomes directly. Applied to classrooms, this raises questions about responsibility when delegated AI tasks contain errors. If artificial intelligence drafts flawed content that a student submits, responsibility becomes genuinely unclear. This contradiction between convenient delegation and clear accountability deserves attention from educational institutions everywhere. Legal liability frameworks developed for algorithmic decisions may offer useful classroom parallels here. Institutions could require students to review and approve delegated AI output before submission. Doing so would preserve delegation benefits while maintaining clear lines of academic responsibility. Policy discussions around algorithmic accountability increasingly extend beyond government and corporate decision-making contexts alone. Education now faces similar questions about oversight when tasks move toward automated systems. This comparison highlights accountability as a key factor shaping fair task delegation practices (AllahRakha, 2025).

Together, these findings offer practical guidance for structuring task delegation within collaborative learning environments. Institutions can identify which tasks safely shift toward artificial intelligence without reducing genuine learning. Teachers can design assignments that reserve reasoning and judgment tasks for direct student work. Students benefit from clearer boundaries showing which contributions require independent, original effort from them. Problem-solving research supports pairing artificial intelligence with structured human oversight during collaborative tasks. This pairing helps maintain educational value while still gaining efficiency from available AI tools. These findings apply directly to policy discussions around responsible classroom AI integration efforts. Universities revising assignment guidelines can reference these delegation patterns when drafting clearer expectations. Departments introducing new generative tools can use this structure to guide early implementation. As task delegation becomes more common, defined boundaries protect fairness and learning quality. These results provide a clear starting point for that necessary classroom design work (Law, 2025).

The whether clearer roles improve accountability within human-AI teams. Groups with explicit task boundaries reported fewer disputes over credit and ownership. This finding carries real significance for how instructors assess collaborative student work fairly. When responsibility stays unclear, grading risks rewarding effort that students did not provide. Clear boundaries let teachers separate genuine student contribution from artificial intelligence assistance. Self-regulated learning research increasingly frames assessment as a shared process involving both parties. Students who monitor their own AI use tend to re-

port responsibility more transparently. This habit connects directly to accountability outcomes observed across collaborative learning settings. Assessment practices built around this awareness could reduce unfair advantages within group projects. Institutions revisiting assessment policy should consider how role clarity shapes honest self-reporting. Recent studies place this question at the center of ongoing assessment reform. These insights support building clearer expectations before students begin collaborative group assignments (O'Dea, 2026).

Supporting evidence comes from language learning groups where artificial intelligence shaped collaborative student behavior. Groups receiving clear guidance about AI involvement showed noticeably more structured collaborative approaches. Students in these groups negotiated task boundaries earlier, before starting shared writing work. This early negotiation reduced later confusion about who contributed which specific part of the assignment. Teachers observed noticeably steadier group dynamics when learners agreed on AI involvement beforehand. Groups without such agreement often revisited disputes about contribution late in the project. This pattern reinforces earlier findings linking role clarity directly to smoother collaborative functioning. It also suggests that guidance works best when introduced before collaborative writing begins. Clear early guidance appears to shape both process quality and eventual accountability outcomes. These findings support introducing structured guidance during initial stages of group project design. Doing so may prevent many accountability disputes that would otherwise surface only near submission deadlines (Rahimi, 2026).

Further evidence comes from research examining how group composition shapes collaboration involving artificial intelligence. Groups with balanced participation treated artificial intelligence as a shared co-author, not a shortcut. This shared framing encouraged members to jointly review and approve AI-generated contributions. Such joint review created a natural accountability checkpoint before content reached final submission. Groups with uneven participation showed clearly weaker collective ownership over artificial intelligence contributions. In these groups, one member often assumed sole responsibility for reviewing machine-generated content. This imbalance sometimes left other members unclear about their own accountability within the project. These findings suggest that group composition itself influences how clearly roles come to function. Balanced participation appears to strengthen the accountability benefits linked to clear role definitions. Instructors forming project groups might consider participation balance alongside skill and subject knowledge. This evidence adds a useful, additional layer showing why clarity alone may not guarantee fairness (Shulgina, 2025).

Some limitations affect how confidently these accountability findings generalize across different classroom environments. Much evidence comes from studies examining teacher roles within specific collaborative learning activities. These studies may not fully capture how peer dynamics alone shape accountability without teacher involvement. Teacher-reported observations also risk reflecting instructor expectations rather than actual student experience directly. Virtual and immersive learning environments introduce additional

complexity not present in traditional classrooms. Role boundaries observed within these virtual settings may not transfer easily to every other context. Sample sizes across many of these studies remain relatively small and quite geographically limited. This limits how broadly findings about accountability and role clarity can be applied. Cultural attitudes toward shared credit and individual responsibility likely vary across regions. Such variation was rarely addressed within the studies reviewed for this section of the analysis. These constraints suggest cautious application rather than universal generalization of accountability findings (Schwartz, 2026).

Comparing these classroom findings with legal research on artificial intelligence reveals a useful contradiction. Legal frameworks generally assign clear and direct responsibility whenever automated systems influence important decisions or outcomes. Classroom practice instead often leaves responsibility loosely defined once artificial intelligence becomes involved. Regulatory approaches developed across Europe emphasize documented accountability for algorithmic decision processes. Applying similar documentation habits within classrooms could strengthen accountability during collaborative student work. Without such documentation, students and teachers may interpret fair contribution in different ways. This gap between legal expectation and classroom practice deserves closer, sustained institutional attention. Policy discussions increasingly connect regulatory accountability principles with everyday educational technology use. Universities updating their academic integrity codes may benefit from reviewing these regulatory accountability models closely. Such review could help translate legal accountability standards into practical classroom expectations directly. This comparison highlights accountability as a shared concern across legal and educational governance contexts (AllahRakha, 2023a).

Together, these findings support clearer institutional guidance for accountability within collaborative learning environments. Institutions can require documented agreements about artificial intelligence involvement before group work starts. Teachers can use these agreements as reference points when assessing individual student contributions. Students benefit from having clear records showing agreed responsibilities within each collaborative assignment. Workplace research on artificial intelligence and human resource management offers a useful parallel here. Organizations increasingly document artificial intelligence involvement to maintain accountability across shared decisions. Classrooms could adopt similar habits to support fair collaborative assessment practices. This applicability extends beyond individual courses toward broader academic integrity policy design. Universities developing new AI usage guidelines can draw directly on these documented practices. Policymakers shaping technology standards may find this accountability model useful. As collaborative AI use grows, documented role clarity becomes necessary across classrooms. These findings provide a foundation for that ongoing institutional development work (Allah Rakha, 2023b).

The students judge fairness when working closely alongside artificial intelligence teammates. Visibility of AI contribution shaped student judgment more than the amount of help received. This finding matters a great deal for designing group activities that feel fair to

every member. When fairness feels absent, students disengage or resent teammates who rely heavily on AI. Physics education research shows that transparent collaboration improves how students value shared problem-solving. Groups solving complex problems together reported stronger satisfaction when contribution remained clearly visible. This visibility principle extends naturally into collaborative learning beyond a single subject area. Fair perception, therefore, depends less on tool use and more on open disclosure. Institutions designing group tasks should treat transparency as a core fairness requirement. Teachers can support this by asking groups to briefly document artificial intelligence involvement. Recent classroom initiatives already encourage such lightweight disclosure practices during ongoing collaborative assignments (Tong, 2025).

Supporting evidence comes from cooperative learning models specifically designed around artificial intelligence assisted roles. These models assign artificial intelligence a defined function alongside clearly stated human responsibilities. Students working within such models reported feeling more comfortable sharing credit with AI. This comfort appeared linked directly to knowing exactly what artificial intelligence contributed to the task. Groups following undefined or informal role structures reported greater unease about fairness in general. The defined model reduced ambiguity that often fuels suspicion toward machine-generated contributions. Students described feeling reassured when artificial intelligence occupied a visible, predictable position within teamwork. This predictability allowed students to judge their own effort against a clear shared standard. Such clarity appears essential for building comfortable, trust-based collaboration involving artificial intelligence partners. These findings support designing similar structured role models across other collaborative subject areas. Doing so could help replicate these positive fairness perceptions in future classroom settings (Tutal, 2026).

Further evidence comes from broader reviews examining dialogue-based learning between students and machine partners. These reviews highlight communication quality as a strong predictor of perceived fairness among students. Groups where artificial intelligence communicated clearly about its own limitations reported higher trust levels. Vague or overly confident machine responses instead increased student suspicion toward shared collaborative work. This pattern reinforces earlier findings connecting transparency directly to positive fairness perceptions. It also introduces communication style as an additional factor shaping student trust levels. Dialogue quality, not only role clarity, appears to influence how fair the collaboration feels. Well-designed conversational interactions can therefore strengthen fairness even within already structured group tasks. These findings suggest that tool design choices carry consequences beyond simple task completion. Developers building classroom-facing AI tools should consider communication clarity alongside functional task performance. This evidence broadens the picture of what genuinely shapes fairness within mixed collaborative teams (Wan, 2026).

Some limitations shape how confidently these fairness findings generalize across different educational contexts. Many available reviews combine findings from short-term studies conducted within single academic terms. Group work risks identified across these reviews

vary widely depending on subject and course design. Findings drawn mainly from writing-heavy or technical courses may not transfer directly elsewhere. Self-reported fairness perceptions also depend on individual student expectations formed before the course began. Students entering with strong prior opinions about artificial intelligence may interpret experiences quite differently. Scoping reviews further note inconsistent methods for measuring fairness across the reviewed literature base. This inconsistency makes direct comparison between separate studies somewhat difficult for researchers currently working. Publication patterns may also favor studies reporting clear or dramatic fairness effects consistently. Quieter or mixed findings could remain underrepresented within the broader published research record. These factors suggest cautious interpretation rather than sweeping conclusions about fairness perceptions (Wei, 2026).

Comparing instructor and peer influence reveals an important contradiction within collaborative fairness research. Some studies suggest instructors shape fairness perceptions mainly through explicit classroom rules and guidance. Other research instead highlights peer behavior as the stronger day-to-day influence on students. Classrooms observing both instructor and peer behavior found peers shaping moment-to-moment fairness judgments directly. Instructors still set the initial framework, but peers reinforce or undermine it constantly. This contradiction suggests that policy alone cannot guarantee fair collaborative experiences for students. Peer culture within each group appears to shape how fairness rules actually get applied. Recent instructional analytics initiatives now track these peer and instructor behaviours together over time. Such tracking could help identify where fairness perceptions break down during ongoing collaborative work. Institutions may need strategies addressing both formal policy and informal peer dynamics together. This comparison highlights fairness as something shaped continuously, not fixed at project start (Xing, 2026).

Together, these findings offer practical direction for supporting fairness within mixed collaborative learning teams. Institutions can pair clear artificial intelligence disclosure policies with attention to peer group dynamics. Teachers can model transparent AI use early, setting expectations before student teamwork begins. Students benefit from structured roles that make artificial intelligence contribution visible and predictable. Self-regulated learning research supports encouraging students to reflect on how AI teammates influence behavior. Such reflection helps students recognize when reliance on artificial intelligence shifts their own effort. These findings apply directly to institutions designing responsible artificial intelligence integration policies today. Universities updating collaborative learning guidelines can reference these fairness patterns when writing new standards. Departments training instructors can highlight both policy design and peer dynamics during preparation. As mixed human-AI teamwork spreads, attention to fairness perception becomes increasingly important everywhere. These findings provide a practical foundation for that ongoing classroom and policy work (Zhang, 2025).

The asks whether artificial intelligence involvement changes measurable student learning outcomes. Findings show that moderate involvement supports engagement, while heavy

reliance weakens independent thinking. This distinction carries real, practical significance for how institutions design AI-supported collaborative coursework. When AI use goes fully unchecked, students risk losing skills that group work should build. Recognizing this balance helps teachers set clear boundaries that protect genuine cognitive development. Bibliometric research tracking AI's impact on cognitive outcomes confirms this pattern across many studies. Researchers increasingly treat learning outcomes as a central concern rather than a side effect. This shift reflects growing awareness that tool access alone does not guarantee learning. Institutions adopting generative tools must therefore pair access with clear pedagogical guardrails. Teachers can use this finding to justify structured reflection requirements within group assignments. Recent research agendas increasingly call for outcome-focused studies rather than simple, surface-level adoption tracking (Ansari & Qamari, 2025).

Supporting evidence comes from research examining creative problem-solving within student-AI collaborative teams. Groups that maintained strong human agency during tasks showed stronger creative learning outcomes. Students who directed the process, rather than following AI suggestions passively, engaged more deeply. This active direction correlated closely with better retention of problem-solving strategies afterward. Passive acceptance of AI-generated solutions instead produced weaker transfer to new, unfamiliar problems. This finding reinforces the earlier pattern linking active engagement to stronger learning outcomes. It also highlights human agency as a specific, measurable factor within that broader pattern. Groups encouraged to question and revise AI suggestions performed better on later independent tasks. This evidence suggests that outcome quality depends on how students exercise control, not just access. Teachers designing assignments should build in moments requiring students to explain their choices. Doing so may help preserve the learning benefits associated with maintained human agency (Guo et al., 2025).

Further evidence comes from research examining shared regulation between students and artificial intelligence partners. Groups practicing joint regulation, where both parties monitored progress, showed stronger learning gains. This co-regulation model encouraged students to reflect closely on their own thinking throughout the task. Reflection appeared to strengthen retention more than simply completing tasks with AI assistance. Groups without shared regulation relied more heavily on artificial intelligence for direct answers. These groups showed weaker performance on later assessments testing independent problem-solving skills. This pattern supports the view that structured interaction shapes outcomes more than tool availability. It suggests that designing collaborative regulation routines could improve learning across various subject areas. Community-based learning frameworks increasingly incorporate artificial intelligence as a monitored, not autonomous, partner. This evidence adds depth to explaining why guided reflective use produced stronger outcomes. Institutions could adopt similar co-regulation routines to support consistent, measurable learning improvement (Pan et al., 2026).

Some limitations affect how confidently these learning outcome findings generalize across all education levels. Scoping reviews examining generative artificial intelligence risks

note uneven study quality across the field. Many studies rely on short-term measures, capturing immediate performance rather than lasting retention. Risks such as reduced critical thinking are often self-reported rather than independently, formally tested. This reliance on self-report may overstate or understate actual learning outcome changes. Reviews focused on younger student populations may not transfer directly to graduate-level coursework. Institutional resources, including access to structured guidance, also vary considerably between different schools. Such variation makes it difficult to isolate artificial intelligence effects from broader resource differences. Risk-focused reviews further note that reporting bias may favor studies showing clear negative effects. Balanced, neutral findings may remain underrepresented within the current body of published research. These constraints call for careful, measured interpretation rather than sweeping generalized conclusions (Tao et al., 2026).

Comparing single-tool studies against multi-agent research reveals an important and genuinely useful contradiction. Single-tool studies often frame AI involvement as one variable, either helpful or harmful. Multi-agent research instead shows that outcomes depend heavily on how agents interact together. Groups working within multi-agent systems distributed learning tasks differently than groups using one simple tool. This distribution sometimes improved outcomes when agents complemented rather than duplicated human effort. In other cases, multiple agents created confusion that reduced measurable learning gains noticeably. This contradiction suggests that agent number and coordination matter just as much as involvement level. It challenges simple assumptions that more AI support automatically produces better learning results. Ecosystem-level research increasingly treats classroom AI environments as complex systems, not single interventions. This complexity should shape how institutions evaluate new AI tools before wider adoption. This comparison highlights coordination as a factor deserving far greater research attention (Xiao et al., 2026).

Together, these findings offer practical direction for protecting learning outcomes within AI-supported coursework. Institutions can require structured reflection points that keep students engaged during tasks. Teachers can design assignments that reward process quality, not merely completed final output. Students benefit from clear expectations about when independent effort matters most. Academic integrity governance work increasingly recommends pairing access policies with active learning safeguards. Such work calls for preventive measures rather than responding only after problems appear. Applying similar thinking here could help institutions design better coursework. This applicability extends beyond individual classrooms toward broader curriculum and assessment policy design. Universities updating teaching guidelines can reference these patterns when setting new standards. Departments introducing generative tools can use this evidence to guide implementation. As AI involvement grows, protecting genuine learning outcomes becomes an increasingly urgent priority. These findings provide a foundation for that ongoing curriculum and policy work (Bădescu et al., 2026).

V. CONCLUSION

Classrooms today increasingly ask students and artificial intelligence to work closely side by side. This shift raises a pressing question about how responsibility should fairly divide between them. Group projects once relied almost entirely on human negotiation, discussion, and shared decision-making. Artificial intelligence now enters that space, actively shaping planning, drafting, and problem-solving together. This change matters because grading, learning, and fairness each depend on clear, defined roles. Without clear structure, students risk unclear credit, unequal effort, and confused accountability within teams. Universities worldwide are already updating policies to address generative artificial intelligence in coursework. These updates show that role distribution is not a narrow, isolated academic concern. It touches assessment integrity, workplace readiness, and how young people learn to collaborate well. As classrooms adopt increasingly capable tools, defining human and machine roles becomes urgent. This research examined that challenge directly, asking how such collaboration can stay fair and effective.

Three connected findings emerged from this research on collaborative learning and artificial intelligence use. First, students and artificial intelligence naturally divide tasks along fairly predictable, observable lines. Drafting and background research often shift toward AI, while final judgment stays largely human. Second, clarity around these roles strengthens accountability and reduces disputes over shared academic credit. Groups with explicit boundaries reported fewer conflicts and clearer, fairer grading outcomes. Third, moderate and reflective artificial intelligence use consistently supported stronger learning than either extreme. Complete avoidance and heavy reliance both weakened genuine student engagement with course material. Together, these findings show that clear structure, not blanket restriction, produces fairer, more effective collaboration. Clear roles helped students trust their teammates, whether human or artificial, more readily. This trust supported deeper learning rather than simple task completion for its own sake. These connected patterns reinforce why deliberate role design deserves close attention in every classroom.

These findings carry real weight beyond individual classrooms and single course assignments alone. As artificial intelligence spreads across education, institutions need workable models for shared, defined responsibility. Clear role frameworks could directly inform academic integrity policy, assessment design, and technology procurement decisions. Recent guidance from universities on generative artificial intelligence already reflects this growing institutional need. Teachers can apply these findings quickly by setting expectations before group projects even begin. Departments can use them to draft disclosure requirements for artificial intelligence involvement in coursework. Beyond classrooms, these patterns may also inform workplace training as human-AI teamwork becomes routine. Future research should examine how these role patterns shift across longer academic programs. Studies following students across multiple academic terms could reveal how delegation habits change. Researchers might also test structured role models directly within diverse classroom settings. This research offers a clear starting point for that necessary and ongoing collaborative effort.

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