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Artificial Intelligence in Interdisciplinary Project-Based Learning: Student Perceptions Across Five Dimensions

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ABSTRACT

This study explores undergraduate perceptions of generative artificial intelligence (AI) within interdisciplinary Project-Based Learning (PBL) in biological sciences courses for non-STEM majors at a Latin-Caribbean university. Using a mixed-methods design, a multidimensional questionnaire assessed five dimensions of AI interaction -cognitive processes, functional interaction, social mediation, personal empowerment, and bridging disciplines- while anecdotal observation cards provided qualitative insights. Analyses confirmed the robustness of the framework, with Functional Interaction valued highest and Social Mediation lowest. Narratives revealed heterogeneous practices, from critical validation to uncritical *dependency, and highlighted creative resistance to AI. Findings suggest that AI enhances technical accuracy and student autonomy but requires deliberate pedagogical scaffolding to strengthen collaboration and foster meaningful interdisciplinary integration in higher education contexts.*

Keywords: Collaboration Challenges, Creative Resistance, Epistemic Engagement, Functional Interaction, Interdisciplinary Integration, Non-STEM Higher Education, Project-Based Learning (PBL), Uncritical Dependency.

INTRODUCTION

The accelerated adoption of generative AI in higher education has outpaced empirical understanding of how students experience AI-supported learning within interdisciplinary project-based science contexts, particularly among non-STEM populations, where available evidence remains more limited compared to STEM-focused settings (Zawacki-Richter et al., 2019).

This gap becomes especially evident in learning designs that emphasize sustained inquiry, student autonomy, and the integration of knowledge across domains, core characteristics of project-based learning (PBL).

PBL has become established as a pedagogical strategy that promotes active student participation, research competencies, and collaborative problem-solving (Thomas, 2000; Hmelo-Silver, 2004). Meta-analyses and systematic reviews confirm that when PBL is designed around authentic challenges and supported by instructional guidance, it fosters disciplinary integration while enhancing creativity and critical thinking in science education (Kwon & Lee, 2025; Simamora, 2024; Strobel & van Barneveld, 2009). This perspective is particularly relevant in the biological sciences, where understanding complex phenomena -such as climate change, global health, and biotechnology- requires approaches that weave together multiple disciplinary perspectives (Kolodner et al., 2003).

Within such learning environments, the presence of generative AI raises open questions about how students engage with inquiry, collaboration, and knowledge integration during project-based work.

Generative AI -including language models, image generators, and code assistants- has rapidly permeated higher education. Recent studies highlight its potential to personalize feedback, enhance writing, and support inquiry, while also cautioning against risks such as over-reliance (Zhai, C. et al., 2024; Zhai, J. et al., 2025), algorithmic bias (Venter et al., 2025), and concerns over authorship and information accuracy (Kasneci et al., 2023; Wang & Fan, 2025). However, empirical research examining how generative AI mediates learning within PBL contexts remains limited, as existing research tends to focus on highly technical fields such as engineering (Lavado-Anguera et al., 2024) or on non-scientific learning contexts (Dai et al., 2025), leaving interdisciplinary biology courses for non-STEM students largely unexplored.

These limitations are further amplified in the Latin-Caribbean context, where empirical studies exploring the role of AI in PBL within undergraduate biology courses for non-STEM students are exceptionally scarce, despite the region's distinctive sociolinguistic, technological, and curricular characteristics (Baudin et al., 2022). As institutions across the region increasingly debate responsible AI adoption in higher education, understanding how students engage with AI during interdisciplinary learning experiences has become a pressing educational and research concern.

Within this context, the PICBio initiative is an interdisciplinary instructional framework designed to engage non-STEM undergraduates in biological sciences through project-based inquiry. The program emphasizes conceptual integration across disciplines and guided, student-driven problem solving, reflecting an interdisciplinary approach that foregrounds the integration of knowledge and perspectives to address complex problems, as suggested by Boix Mansilla (2010, 2016). This instructional design provides a natural setting in which AI tools -such as ChatGPT, programming assistants, and image generators- are used for ideation, organization, and task support. While prior implementation of PICBio documented gains in student motivation and conceptual integration, they did not examine how students perceive the influence of AI on creativity, collaboration, and interdisciplinary integration (Ortiz-Andrade, 2025).

Addressing this gap, the present study investigates how non-STEM undergraduates perceive AI's influence on creativity, collaboration, and interdisciplinary integration during PBL in a biology course. Specifically, it analyzes five dimensions of interaction: (1) cognitive processes, (2) functional interaction, (3) social mediation, (4) personal empowerment, and (5) bridging disciplines. Using a mixed-methods approach, the study combines factorial and descriptive analysis of a multidimensional questionnaire with thematic analysis of observational records (Braun & Clarke, 2006). Beyond assessing the psychometric robustness of this five-dimension model, the study identifies emergent categories -such as creative resistance to AI and uncritical dependency- that provide deeper insight into how students navigate AI-supported interdisciplinary projects.

RESEARCH METHOD

This study employed an exploratory mixed-methods design to examine undergraduates' perceptions of generative AI tools within Project-Based Learning (PBL). Quantitative analyses included descriptive statistics, inferential tests, and exploratory factor analysis, while qualitative data were examined through thematic analysis. The research was conducted during the Spring 2025 semester and the

Summer 2025 term at a Latin-Caribbean public university where Spanish is the dominant language, in two biology courses for non-STEM students.

Participants

A total of 73 undergraduate students participated in different phases of the project, with 57 completing the questionnaire (78% response rate). Although the courses are in Biological Sciences (STEM), they are part of the General Studies College and are taken by non-STEM majors. Therefore, all participants were non-STEM undergraduates from fields such as Humanities, Social Sciences, and Business Administration.

Most respondents were between 21 and 23 years old (59.6%), followed by those aged 18–20 (33.3%). In terms of gender, 70.2% identified as women, 28.1% as men, and 1.8% as nonbinary. Participants ranged from first-year to fifth-year and beyond, with the largest groups in the fourth year (29.8%) and fifth year or higher (28.1%). This heterogeneous composition reflecting a range of academic backgrounds and experience, provided a robust basis for analyzing AI use across diverse academic contexts.

Instruments

The twelve-item questionnaire was designed drawing on prior frameworks of AI in education and interdisciplinary learning (Boix Mansilla, 2010; Popenici & Kerr, 2017), and refined to capture five theoretical dimensions: (1) Cognitive Processes, (2) Functional Interaction, (3) AI as a Social Mediator, (4) Personal Empowerment, and (5) Bridging Disciplines (Table 1). Sociodemographic questions (gender, major, and academic year) were also included.

In addition to the twelve items grouped into the five theoretical dimensions, the questionnaire included a separate item asking students to evaluate the level of disciplinary integration achieved in their projects. This item did not form part of the five-dimension framework but was analyzed independently to explore its association with overall AI use.

Complementing the questionnaire, a qualitative component was implemented through anecdotal observation cards. Between three and five cards were documented per session across five key PBL stages mentioned in section 2.3. Each card documented the project phase, observed behaviors (e.g., interactions with AI, team dynamics, expressions of autonomy, or technical challenges), relevant dialogue excerpts, and the observer’s analytical reflections.

Table 1
Questionnaire items by theoretical dimension

Dimension	Description	Items
1. Cognitive Processes (*Cognitive Interaction*)	Relates AI use to creativity, judgment, and ethical reflection.	• I used AI to generate original ideas. • AI facilitated design but reduced my personal creativity. • I reflected on the ethical limits of AI use.
2. Functional Interaction (*Technical and Critical*)	Explores the student's ability to operate the tool, validate results, and overcome barriers.	• I verified AI information with other sources. • I had difficulties identifying errors in AI information. • I encountered technical barriers when using AI.
3. AI as a Social Mediator (*Collaborative Interaction*)	AI as a tool that supports teamwork and group organization.	• AI improved collaboration within the team. • AI helped distribute tasks more effectively.
4. Personal Empowerment (*Autonomous Interaction*)	Assesses how AI strengthened the student's autonomy and confidence.	• AI increased my autonomy for research. • I felt more confident in my work because of AI.
5. Bridging Disciplines (*Epistemic Interaction*)	Evaluates the role of AI in integrating knowledge and generating interdisciplinary products.	• AI helped integrate biological sciences with other disciplines. • The product reflected interdisciplinary connections supported by AI.

Procedure

The PBL intervention was implemented in two formats depending on the academic term. For students enrolled in the regular semester, the intervention lasted 14 weeks, while for students enrolled in the summer course, it was condensed into 4 weeks. Both versions followed the same five-stage sequence: (1) orientation and topic selection, (2) initial inquiry, (3) product design and development, (4) preparation of the presentation, and (5) public presentation of results.

Participation was voluntary, and informed consent was obtained in accordance with institutional ethical guidelines.

Students were organized into 20 interdisciplinary teams of three to four members. Group composition was arranged so that students from related majors were clustered together, facilitating the integration of disciplinary perspectives within each team.

Throughout the intervention, students were free to use any AI tools they considered relevant, including large language models, translation applications, content design platforms, or image generators. Instructors provided scaffolding to ensure that AI use aligned with pedagogical goals, emphasizing critical validation, ethical reflection, and verification of outputs.

Anecdotal observation cards were collected during the intervention to capture student behaviors, dialogues, and team dynamics related to AI use. Completed exclusively by the course professor, as specified in the human-subjects research protocol, these cards provided qualitative insights that complemented the quantitative data.

All final products were required to integrate biological sciences with at least one additional disciplinary perspective. Outputs included interactive databases, blogs, websites, posters, videos, brochures, educational games, prototypes, draft bills, and creative campaigns.

This procedure ensured that all students experienced the full PBL cycle, integrating disciplinary perspectives, applying AI tools according to their needs, and presenting authentic interdisciplinary products.

Data analysis

Quantitative analyses were conducted at two levels. First, items were grouped into their corresponding theoretical dimensions -Cognitive Processes, Functional Interaction, AI as a Social Mediator, Personal Empowerment, and Bridging Disciplines- based on the instrument's design. For each participant, an average score per dimension was calculated by aggregating responses to the relevant items, thus preserving the original 1–5 Likert scale. Second, an overall AI use index was computed as the mean of all 12 items, providing a global measure of students' engagement with AI. In addition to the twelve items grouped into the five theoretical dimensions, the separate item about the level of disciplinary integration achieved in their projects (levels ranged from 1 = no interaction to 4 = solid integration) was analyzed independently to explore its association with overall AI use.

Descriptive statistics (Mean, SD) were calculated for each dimension and for the global index. Pearson correlations among items and dimensions were examined, and exploratory factor analysis (EFA) was conducted to test construct validity, adopting $r \geq 0.40$ as the threshold for item–dimension correlations. Because the scale was applied to a modest sample ($N = 57$), factorial validation was approached in an exploratory manner, consistent with methodological recommendations for early-stage studies (Costello & Osborne, 2005). Internal consistency was assessed using Cronbach's alpha for the full scale ($\alpha = 0.81$) and for each dimension separately, with coefficients ≥ 0.70 considered acceptable.

Independent-samples t-tests were used to examine potential differences between Group 1 (regular semester, 14 weeks) and Group 2 (summer session, 4 weeks). As no statistically significant differences were observed, responses were analyzed jointly.

Qualitative analysis was based on thematic coding of anecdotal observation cards following Braun and Clarke’s (2006) framework. Codes were aligned with the five theoretical dimensions (e.g., AUT for autonomy, TEC for technical barriers), while also allowing emergent themes to surface. Since the classroom professor was the sole observer, as specified in the human-subjects research protocol, triangulation with quantitative data was employed to strengthen validity and reduce potential observer bias.

The integration of quantitative and qualitative results provided a comprehensive view of student–AI interactions, capturing both statistical patterns and contextualized learning experiences.

RESULTS

The results are organized into six sections: (1) validation of the theoretical structure, (2) reliability of the instrument, (3) descriptive statistics of AI interaction dimensions, (4) correlations among dimensions and with disciplinary integration, (5) qualitative findings from anecdotal observation cards, and (6) integration of quantitative and qualitative results.

Validation of the Theoretical Structure

Exploratory factor analysis supported the grouping of the 12 questionnaire items into the five theoretical dimensions of interaction with AI. Pearson correlation coefficients between each item and its proposed dimension exceeded the $r \geq 0.40$ threshold in nearly all cases, indicating adequate construct validity. Particularly high values were observed in Functional Interaction (up to $r = 0.93$), Personal Empowerment (up to $r = 0.91$), and Social Mediation (up to $r = 0.90$), as presented in Figure 1. Only three items fell below the threshold: *AI facilitated design but reduced my personal creativity* ($r = 0.32$), *AI helped distribute tasks more effectively* ($r = 0.35$) and *The product reflected interdisciplinary connections supported by AI* ($r = 0.23$).

Figure 1

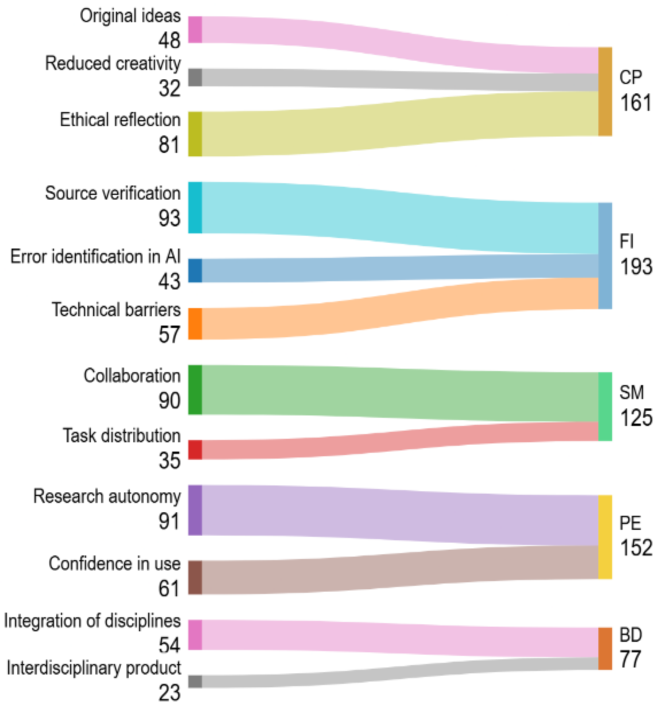
Heatmap of Pearson Correlations Between Questionnaire Items and AI Interaction Dimensions

Note. The heatmap displays Pearson correlation coefficients (*r*) between the 12 questionnaire items and the five AI interaction dimensions: CP = Cognitive Processes; FI = Functional Interaction; SM = AI as a Social Mediator; PE = Personal Empowerment; BD = Bridging Disciplines. Color intensity ranges from low correlations (gray) to high correlations (yellow). *N* = 57.

Visual representations reinforce the robustness of the framework: the heatmap highlights strong item–dimension associations, while a Sankey diagram (Figure 2) illustrates how items flow into their respective dimensions. The diagram makes clear that Functional Interaction accumulated the largest weight, while Social Mediation also showed consistently strong associations, underscoring its role in teamwork and task organization. In contrast, Bridging Disciplines reflected more modest but still meaningful connections, highlighting variation in how students experienced AI across dimensions.

Figure 2

Sankey Diagram of Questionnaire Items and AI Interaction Dimensions



Note. The Sankey diagram shows the association between the 12 questionnaire items (left) and the five theoretical dimensions of AI interaction (right): CP = Cognitive Processes; FI = Functional Interaction; SM = AI as a Social Mediator; PE = Personal Empowerment; BD = Bridging Disciplines. Line width is proportional to Pearson's r values for item–dimension correlations.

Reliability of the Instrument

The internal consistency of the instrument was satisfactory, with a Cronbach's alpha of 0.81 for the full 12-item scale. Reliability coefficients for each dimension also reached acceptable values ($\alpha \geq 0.70$), supporting the stability of the measurement model.

A comparative analysis between the two student groups (regular semester vs. summer course) revealed no statistically significant differences across the 12 AI-related items (all $p > 0.05$). These results suggest that course modality did not substantially influence students' perceptions or uses of AI during the PBL intervention.

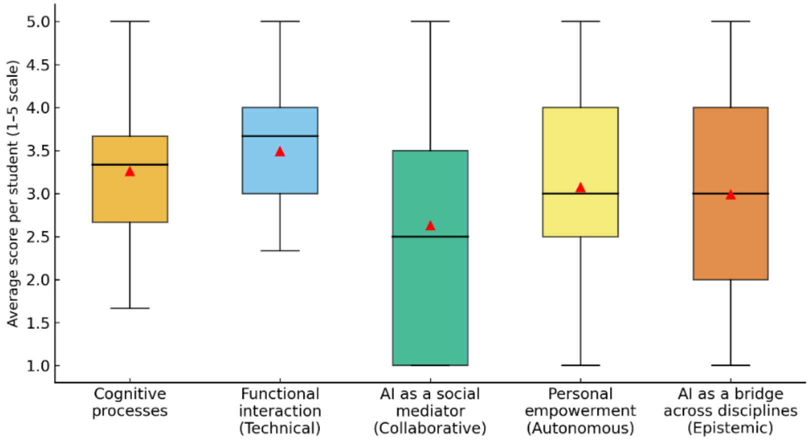
Descriptive Statistics of AI Interaction Dimensions

Students assigned the highest mean scores to Functional Interaction (M = 3.71, SD = 0.78), followed by Personal Empowerment (M = 3.07, SD = 0.68) and Bridging Disciplines (M = 2.99, SD = 1.22). Cognitive Processes (M = 2.89, SD = 1.10) and AI as a Social Mediator (M = 2.89, SD = 0.83) obtained comparatively lower scores (Figure 3), though still close to the midpoint of the scale. The distribution of scores across dimensions, illustrated by boxplots, showed moderate variability, with Functional Interaction emerging as the most consistently valued aspect of AI use.

Descriptive statistics and visualizations (Figure 3) also revealed distinctive patterns within dimensions. In Cognitive Processes, responses were contrasting: some students reported that AI enhanced their creativity and ethical reflection by facilitating idea generation, whereas others perceived a reduction in their personal creativity. The median score was located near the center of the scale, pointing to an overall intermediate perception of this dimension. Functional Interaction displayed moderate dispersion, with some participants experiencing technical barriers when using AI tools, while others were able to critically verify and validate information. These differences reflected variation in prior technological competencies and familiarity with AI. Social Mediation showed the lowest overall values, suggesting that AI was used primarily for individual activities rather than as support for group dynamics. In contrast, Personal Empowerment showed moderate scores, indicating that students perceived AI as somewhat strengthening their research autonomy. Finally, Bridging Disciplines obtained intermediate values, reflecting that while AI contributed to connecting biological sciences with other areas of knowledge, its integrative potential was not rated as highly as other functions.

Figure 3

Boxplots of Student Scores Across Five AI Interaction Dimensions



Note. The boxplots display the distribution of student scores across the five AI interaction dimensions on a 1–5 Likert scale. The horizontal line represents the median, the box indicates the interquartile range, the whiskers show minimum and maximum values, and the red triangle denotes the mean. Scores range from 1 (strongly disagree) to 5 (strongly agree).

Correlations among Dimensions and with Disciplinary Integration

Significant positive correlations were observed between overall AI use and each of the five dimensions: Cognitive Processes ($r = 0.82$, $p < 0.001$), Functional Interaction ($r = 0.48$, $p < 0.001$), Social Mediation ($r = 0.64$, $p < 0.001$), Personal Empowerment ($r = 0.44$, $p = 0.001$), and Bridging Disciplines ($r = 0.84$, $p < 0.001$). These results suggest that students who reported higher levels of AI use also perceived stronger impacts across cognitive, technical, collaborative, autonomous, and epistemic domains. By contrast, a weak negative correlation was found between overall AI use and the independent item measuring disciplinary integration (Pearson $r = –0.25$, $p = 0.057$; Spearman $\rho = –0.26$, $p = 0.047$), indicating that higher AI use was slightly associated with lower levels of interdisciplinary integration. At the same time, the item Research autonomy displayed a strong positive correlation with Bridging Disciplines ($r = 0.92$), suggesting that the quality and context of AI use, rather than its frequency, may be more decisive for its contribution to interdisciplinarity.

Qualitative Findings from Anecdotal Observation Cards

The thematic analysis of 28 anecdotal observation cards provided qualitative insights that complemented the quantitative results. Within the dimension of Cognitive Processes, students reported using AI for idea generation during brainstorming phases, while others resisted relying on AI for creative tasks, an emergent stance later described as creative resistance. Beyond this cognitive aspect, students also engaged with AI in more technical and evaluative ways, captured under the dimension of Functional Interaction. Functional Interaction included practices such as verifying AI-generated references, identifying errors, or, conversely, displaying uncritical dependency on automated outputs. In Social Mediation, AI was used in a wide variety of tasks -from idea generation and presentation design to plant identification and translation of technical terms (differentiated domains of application)- yet they also encountered gaps in mediated collaboration, indicating limited appropriation of AI as a teamwork resource. Personal Empowerment was evidenced through autonomous use of AI tools, including spontaneous searches with assistants like Siri and stylistic revision of texts. Nevertheless, preferences for AI use were shaped by device availability, producing distinct access channels. Finally, Bridging Disciplines was reflected in interdisciplinary applications such as plant identification using AI apps, translation of scientific terminology, and creative integration of biology with other domains.

Illustrative products highlighted students' creativity and interdisciplinary reach. For instance, one group designed an interactive biodiversity database in Power BI that integrated biological sciences with information systems, accounting, and tourism. Another developed a sustainability-focused blog that combined biology with marketing and social work to promote ecological lifestyles. A third group produced a multilingual brochure on pollination and the carpenter bee (Xylocopa mordax), translated into Spanish, English, Mandarin, and French, showcasing links between biology, linguistics, and creative writing.

Beyond these predefined dimensions, emergent categories highlighted the heterogeneous ways in which students positioned themselves in relation to AI. Among these, some groups resisted its use, relying on their own creativity. We define this stance as creative resistance to AI, referring to students' deliberate refusal to use AI for idea generation or design, motivated by the conviction that doing so would diminish their originality and authorship. For instance, one group explicitly rejected AI prompts in favor of their own brainstorming process. In contrast, other students integrated AI definitions and summaries without verification (uncritical dependency).

Overall, these qualitative categories (Table 2) reinforced the quantitative profile across dimensions. Intermediate scores in Cognitive Processes were mirrored by both creative idea generation and resistance to AI, while Functional Interaction aligned with practices of verification and occasional uncritical use. Personal Empowerment and Bridging Disciplines matched narratives of autonomy and interdisciplinary integration, and the lowest values in Social Mediation were consistent with reported gaps in AI-assisted collaboration.

Table 2

Categories from thematic analysis of anecdotal cards, organized by AI interaction dimensions

Dimension	Categories	Operational definition
1. Cognitive Processes	Creative idea generation	Use of AI for brainstorming when initial inspiration is lacking
	Adjustment and reflection	Discussion and critical refinement of AI-generated suggestions
	*Creative resistance to AI /skepticism	Refusal to delegate creativity to AI, based on confidence in one's own originality
2. Functional Interaction (technical / critical)	Source verification	Searching external sources or studies to confirm and support AI-generated information
	Error identification and	Detecting and manually correcting inaccuracies in AI-generated references.

	validation awareness	
	*Uncritical dependency	Acceptance of AI definitions without verification
3. AI as a Social Mediator (collaborative)	Support in presentations	Use of AI to generate text and design slides in group work
	Gaps in mediated collaboration	Uncertainty about how to use AI for team coordination
	Use of AI in presentation titles	Reliance on AI to generate creative and attractive titles for group presentations
4. Personal Empowerment (autonomous)	Spontaneous searching	Immediate consultation of assistants (Siri, ChatGPT) without external guidance
	Autonomy in style revision	Use of AI to correct style and grammar in personal texts
	Device-based preferences	Choice of AI tool depending on available devices (smartphone, tablet, laptop)
5. Bridging Disciplines (epistemic)	Interdisciplinary integration	Combining biology with other disciplines in idea generation
	Species identification	Use of AI-based apps to recognize plants and compare structures
	Translation of technical terms	AI used to translate complex scientific terminology
	Differentiated domains of application	Use of AI for varied tasks (web design, business, etc.)

*Emergent categories

Integration of Quantitative and Qualitative Results

The convergence of quantitative and qualitative findings underscored the complexity of student–AI interactions. Intermediate scores in Cognitive Processes were consistent with narratives of both creative idea generation and resistance to AI use. Functional Interaction results aligned with accounts of error detection, verification, and occasional uncritical dependency. Lower values in Social Mediation matched qualitative evidence of gaps in AI-supported collaboration. Meanwhile, moderate ratings in Personal Empowerment and Bridging Disciplines were reflected in students' narratives of autonomous research practices and interdisciplinary applications. Overall, the integration of results highlights that the quality of AI engagement -particularly when linked to autonomy and critical validation- can enhance interdisciplinary integration, whereas uncritical or excessive reliance on AI may constrain it.

DISCUSSION

This study supported the validity and reliability of a five-dimension framework for analyzing student interaction with AI in project-based learning. Results showed the highest scores in Functional Interaction and the lowest in Social Mediation, with qualitative narratives reinforcing these patterns and revealing heterogeneous positions toward AI.

Quantitative results indicated that participants valued Functional Interaction the most (M = 3.71), followed by Personal Empowerment (M = 3.07), while Bridging Disciplines (M = 2.99), Cognitive Processes (M = 2.89) and AI as a Social Mediator (M = 2.89) received comparatively lower ratings. This profile is consistent with prior studies where AI was primarily perceived as a technical aid and a confidence-building tool, while its collaborative and epistemic potential remained underdeveloped (Walter, 2024; Zawacki-Richter et al., 2019). The intermediate score of Bridging Disciplines suggests that while AI facilitated some interdisciplinary practices, its epistemic potential was not uniformly recognized across teams (Cai et al., 2024).

The qualitative findings complement and deepen this perspective. In the dimension of Cognitive Processes, AI functioned as a creative trigger in brainstorming stages (“Look, let’s search for ideas in ChatGPT… Go ahead”), while also fostering reflective refinement when groups critically adjusted AI-generated suggestions (“They then started making adjustments…”). These observations support claims that AI can enhance both creativity and critical thinking when paired with reflective scaffolding (Walter, 2024; Yang et al., 2025). At the same time, some students resisted using AI for creative tasks -creative resistance to AI- defined here as students’ active refusal to use AI where originality was perceived as central. This extends previous accounts of resistance to technology in creative domains (Xu, 2025; Yonggang et al., 2024) by situating such resistance within PBL contexts.

Creative resistance was observed primarily among students in the arts. Within this group, such resistance manifested across multiple dimensions of their productions, including stop-motion animations, original voiceovers in videos, drawings, character design, and, notably, the titles of their presentations. Although the proportion of art students within the sample was too small to support more in-depth statistical analysis, this stance was clearly identifiable both in their discursive expressions and in the direct examination of their artifacts, which showed minimal or no use of generative AI tools in the creative components. From this perspective, creative resistance may be understood as reflecting students´ concerns about authorship and originality in creative work, rather than as a general rejection of technology.

This interpretation resonates with philosophical and certain legal discussions that conceptualize artistic creation as closely tied to the author´s identity (Ley de Derechos Morales de Autor de Puerto Rico, 2012; Kemp, 2021), although these frameworks are not directly examined in the present study. Accordingly, these findings should be considered exploratory and point to the need for further empirical research on creative authorship and AI in PBL contexts.

Regarding Functional Interaction, students demonstrated both vigilance and vulnerability. Several reported manually checking APA references to ensure their accuracy ("Five students noted that AI generated errors…"), reflecting error awareness. In contrast, others accepted AI definitions or summaries without verification -an uncritical dependency that underscores the importance of cultivating critical judgment of automated outputs- ("Two students… were not seen conducting additional searches…") and the lack of information competencies as presented in Popenici and Kerr (2017). These polarized practices highlight that digital literacy is not evenly distributed and must be deliberately developed in PBL contexts.

This concern becomes evident when students fail to critically evaluate the sources of the scientific information they use, placing educators in the position of confronting a new and emerging source of information, one that contributes to the concerns underlying faculty resistance to generative AI presented in Shata (2025). The issue no longer lies solely in inaccurate content disseminated through social media or other communication channels; rather, it now includes AI-generated information that is consciously and intentionally incorporated by students as a tool for academic inquiry, despite its documented susceptibility to errors and hallucinations already object of recent research (Salvagno et al., 2023). This phenomenon underscores the need to strengthen critical source-evaluation skills and scientific literacy, now explicitly incorporating the responsible use of artificial intelligence within educational practices.

The dimension of AI as a Social Mediator revealed that many groups used AI to co-create content and designs in Canva, which streamlined the preparation of presentations ("Several students created the presentation in Canva…"). However, some teams acknowledged not knowing how to employ AI to coordinate roles or integrate contributions ("Several groups faced collaboration problems…"), suggesting that effective social mediation requires specific instructional design (Walter, 2024; Zhang et al., 2022). The lower quantitative scores in this dimension were consistent with these qualitative gaps in collaborative appropriation. Importantly, such difficulties are not unique to AI but reflect long-standing challenges in project-based learning, including unequal participation, ambiguous task assignments, and coordination breakdowns as reported in Hussein (2021) and Zhang et al (2023;), and more prominently when exploring it in online group projects like in Donelan & Kear (2024). Similar dynamics have also been documented in prior work with interdisciplinary projects in biological sciences, where students struggled to balance the preservation of their disciplinary identity with the need to collaborate across fields in shared interdisciplinary products (Ortiz-Andrade, 2025). Taken together, these findings suggest that AI has not resolved the structural challenges of teamwork in PBL, though its potential to act as an organizational facilitator -through role assignment, workflow management, and communication support- remains promising if paired with explicit pedagogical scaffolding.

In terms of Personal Empowerment, students independently consulted assistants such as Siri or ChatGPT (“A student grabbed their phone and immediately asked Siri…”), and used AI to refine the style and grammar of their texts (“One student… asked AI to review their summary”), reinforcing their confidence in writing tasks. This pattern aligns with the moderate mean score (M = 3.07), confirming that empowerment was present but not uniformly strong. Preferences for specific AI tools were also shaped by device availability, creating distinct access channels (e.g., phone, tablet, or laptop).

Turning to the last dimension, Bridging Disciplines was reflected in practices such as using AI-based apps to identify plants (“Students used AI from some applications to identify plants…”) and translating technical terms for intercultural tasks (“To translate a pamphlet on a Puerto Rican bee into Mandarin…”). These examples illustrate AI’s role as a connector of knowledge and specialized languages, supporting interdisciplinarity. Nevertheless, the moderate scores in this dimension highlight that such integration was not equally achieved by all teams, aligning with the weak negative correlation observed between overall AI use and perceived disciplinary integration. It is important to note that this measure of disciplinary integration derived from a single independent item rather than from the multidimensional scale and was therefore analyzed separately as a complementary indicator. Students also applied AI in differentiated domains of application, including website development, marketing ideas, and artistic products, illustrating its versatility beyond traditional academic tasks.

At the same time, the strong positive correlations between overall AI use and all five dimensions -Cognitive Processes, Functional Interaction, Social Mediation, Personal Empowerment, and Bridging Disciplines- indicate that students who reported greater AI use also perceived stronger impacts across cognitive, technical, social, autonomous, and interdisciplinary domains. This dual finding not only reinforces the internal coherence of the five-dimension framework -since higher AI use was consistently associated with stronger perceptions across all domains- but also suggests that quantity of use alone is insufficient for fostering integration. Instead, its contribution to genuine interdisciplinary outcomes may depend on explicit pedagogical mediation.

This finding underscores that the pedagogical challenge is not simply to increase students’ frequency of AI use but to shape the quality of that engagement. When AI use was framed as a means of fostering research autonomy, it strengthened interdisciplinary integration; however, when engagement was uncritical or excessive, it appeared to constrain meaningful connections across disciplines. Designing tasks that explicitly channel AI-supported autonomy toward integrative goals therefore becomes essential.

Exploratory factor analysis supported the robustness of the five-dimension structure, with item-dimension correlations exceeding r = 0.40 in nearly all cases, except for three items recommended for revision without eliminating their conceptual value, as suggested by Clark and Watson (2016) and DeVellis and Thorpe (2022). The factorial structure obtained here not only validates the five-dimension framework but also provides a replicable basis for future measurement of AI–learning interactions in PBL contexts. Together, the quantitative and qualitative findings provide an empirical and narrative basis for designing instructional interventions and guiding the effective integration of AI in PBL contexts. These insights also resonate with current institutional frameworks that call for responsible and pedagogically grounded AI adoption in higher education.

Finally, the interdisciplinary products created by students exemplify deeper levels of integration, most of them transdisciplinary in nature. At the outset, disciplinary boundaries were clearly marked between students' non-STEM majors and the biological sciences course. However, as projects advanced, these boundaries blurred, resulting in products where the disciplinary contributions were no longer easily distinguishable. For instance, students created a biodiversity database in Power BI that integrated biological sciences with information systems, accounting, and tourism; a sustainability-focused blog that combined biology with marketing and social work to promote eco-conscious lifestyles; and a multilingual brochure on pollination translated into Spanish, English, Mandarin, and French that merged biology with creative writing and linguistics. Similarly, proposals for eco-stores, pollinator gardens, and nonprofit organizations illustrated how students connected biological sciences with business, architecture, and social sciences. These products suggest that, through iterative collaboration and AI-supported ideation, students moved from juxtaposing disciplines to producing outputs where the limits of each field became less visible, reflecting genuinely integrative -and in most cases transdisciplinary- outcomes, consistent with Boix Mansilla's (2010, 2016) characterization of deep interdisciplinary learning.

CONCLUSIONS

This study suggests the validity and reliability of a five-dimension framework for analyzing student interaction with AI in project-based learning. The factorial structure not only proved robust but also offers a replicable basis for future measurement of AI–learning interactions. Results showed that students perceived AI primarily as a tool for technical support and individual autonomy, as reflected in the highest scores for Functional Interaction and moderate ratings for Personal

Empowerment. In contrast, the lowest values in Social Mediation highlighted persistent challenges in teamwork, suggesting that AI has not yet overcome the structural difficulties of collaboration traditionally reported in project-based learning.

Bridging Disciplines, combined with a weak negative correlation between overall AI use and perceived disciplinary integration, indicates that interdisciplinarity does not occur automatically through the use of intelligent tools. At the same time, the strong positive correlation between research autonomy and interdisciplinary integration underscores that the quality and context of AI engagement, rather than its quantity, may be decisive for transforming outputs into meaningful cross-disciplinary connections. The study also revealed that through project-based learning, students not only integrated biological sciences with their non-STEM fields but, in most cases, developed products where disciplinary boundaries were blurred, reflecting transdisciplinary potential.

Overall, the findings indicate that while AI can enhance creativity, technical accuracy, and academic autonomy, its full potential in PBL depends on deliberate instructional design. Clear protocols for collaboration, digital literacy training, and structured opportunities for interdisciplinary integration are essential to ensure that AI becomes not only a technical assistant but also a catalyst for collective and epistemic learning. These conclusions also resonate with broader educational frameworks that call for responsible and pedagogically grounded AI adoption in higher education.

RECOMMENDATIONS

To address students' creative resistance to AI and uncritical dependency, activities should showcase successful cases of human–AI co-creation and include rubrics that prompt systematic validation of outputs, supported by digital literacy modules to detect errors such as inaccurate references or overgeneralized summaries. Given the strong scores in Functional Interaction, PBL designs should incorporate progressively complex tasks that foster critical evaluation of AI reliability, while ensuring task–technology fit. The low values in Social Mediation highlight the need for clear collaboration protocols so AI supports equitable teamwork. Finally, the moderate results in Bridging Disciplines and the weak negative correlation with interdisciplinary integration indicate that pedagogical mediation is essential to translate AI-supported outputs into meaningful interdisciplinary connections. Although these findings emerged in Biological Sciences, they suggest transferable practices for other fields, reinforcing the interdisciplinary spirit of project-based learning.

LIMITATIONS

The exploratory scope of this study, conducted in a single institutional context with a modest sample size, may constrain the generalizability of its findings. The reliance on self-reported measures and anecdotal observation cards also introduces subjectivity, although triangulation with quantitative results mitigated this limitation. The participant-to-item ratio (~5:1) meets minimal recommendations for exploratory factor analysis (Costello & Osborne, 2005), but following guidance from Fabrigar et al. (1999) and DeVellis and Thorpe (2022), results should be regarded as preliminary evidence of construct validity and warrant replication with larger samples. Furthermore, the use of averages to capture dimensions may mask individual variations in AI engagement, while the absence of longitudinal data precludes analysis of sustained effects over time.

FUTURE DIRECTIONS

Future research should examine in depth the factors underlying creative resistance to AI, such as disciplinary identity and academic self-efficacy, to better understand why some students reject AI in cognitive and creative tasks. It would also be valuable to quantify uncritical dependency by systematically evaluating how lack of verification affects the quality of student products and to design training strategies accordingly. The development and validation of instruments to measure AI literacy, error awareness, and collaboration skills will allow more precise evaluation of targeted interventions.

Additionally, given the low ratings in Social Mediation, experimental studies should explore AI-assisted group coordination models, with clearly defined roles, real-time feedback, and workflow supports, to determine how collaboration can be optimized. Considering the moderate perception of Bridging Disciplines, further research should analyze how explicit interdisciplinary scaffolds (e.g., structured cross-disciplinary prompts or integrative assignments) interact with AI use to support knowledge integration. Finally, cross-institutional and longitudinal studies with larger cohorts are needed to test the robustness of the five-dimension framework and to refine its application in diverse educational contexts.

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