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Practical experiences of artificial intelligence in science clubs

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The 21st century presents us with knowledge and technologies like AI introducing new educational possibilities to improve human talent and performance. In recent years there has been an increase in the literature on artificial intelligence in education and research opportunities with practical experiences in communities in emerging countries. This study investigates how participation in science clubs focused on AI-related projects supports the development of complex thinking and scientific thinking among high school and university students. Drawing on a multiple case study design, the research analyzes six cases involving 83 students across four Mexican cities, all engaged in science clubs jointly organized by academic teams from Mexico and the United States. The results show that (a) participants in all analyzed cases of practical applications of AI demonstrated a high perceived level of complex thinking competency; (b) although no statistically significant differences were found, women, on average, tended to report slightly higher perceptions of complex thinking development compared to their male counterparts; and (c) a similar non-significant trend was observed for scientific thinking, with women reporting marginally higher self-perceived levels than men. These insights contribute to the global conversation on integrating AI into non-formal education to cultivate transversal cognitive skills applicable across diverse educational contexts.

KEYWORDS

complex thinking, educational innovation, higher education, artificial intelligence, science clubs

1 Introduction

Artificial intelligence (AI), which integrates algorithms through processes and machines, can promote human capabilities and holds potential to support development in emerging countries. On the one hand, at the educational level, Douali et al. (2022) state that, in developing countries, AI is used in almost all tasks of daily life and holds promise for accompanying educational tasks in the provision of technical assistance during teaching. On the other hand, on the research level, there is a need for AI applications to be more thematically diversified and deeper (Paek and Kim, 2021), both in the understanding of knowledge and in the applications of generative artificial intelligence (Hwang and Chen, 2023), and ChatGPT (Hsu and Ching, 2023). This opens a field for educational research from multidisciplinary and multi-contextual perspectives to address the complexity of the pressing changes.

In this scenario of urgent and intertwined transformations, science clubs emerge as living spaces of pedagogical experimentation, where knowledge, curiosities and real-world problems converge. More than extracurricular activities, they represent citizen laboratories of collaborative learning, where students, teachers, and communities try out creative responses to contemporary challenges. In line with this delimitation of science clubs, López-Caudana et al. (2025) mention that, despite variations in Science Clubs, common characteristics are found that emphasize interactive learning and hands-on engagement. In a focus on analyzing teachers' participation in science clubs, Martín-García et al. (2024) found that the learning acquired in science club activities complements and broadens teachers' experience and contributes to their professional development in all three dimensions: personal, social, and professional. Similarly, Rahm (2025) analyzed urban science clubs and another involving a community-led water stewardship program, finding science practices that are locally relevant, transformative and empowering, and deeply committed to social justice. The potential of science clubs lies in articulating diverse contexts and multiple disciplines, making them privileged nodes for investigating how educational innovation is configured in authentic and meaningful situations.

Collaborative work through academic networks, allows possibilities for the interaction of diverse countries and institutions, in a cooperative and supportive manner, to address the new challenges presented by society. Socially responsible research and implementation of AI in education systems (Schiff, 2021), with collaboration between educators, developers and researchers (Bhimdiwala et al., 2021), needs to be encouraged. Specifically, Wang and Cheng (2021) invite Learning from AI, learning about AI and Learning with AI, where barriers should lead to prioritizing efforts to remove or reduce them.

In this context, the present article analyzes cases of practical educational applications of AI carried out through the collaborative work of science clubs organized by academics from the United States and Mexico, with the objective of fostering the development of scientific thinking and complex thinking among high school and university students. In Mexico, science clubs originated from the innovative ideas of students committed to advancing science and technology, leading to the creation of a network that brings together people from different countries, institutions, and educational levels. Their mission is to democratize education and expand the intellectual horizons of future generations by providing practical experiences from the Global South that can be adapted and transferred to other contexts.

2 Theoretical framework

2.1 Potentialities and risks in the application of artificial intelligence in education (AIED)

The ways of teaching and learning have been transformed throughout history. Various technologies have been used to achieve effectiveness in these processes, and the 21st century presents new alternatives with artificial intelligence. Potential is found in intelligent tutoring systems and massive open online courses (Feng and Law, 2021), as well as in adaptive learning, teaching assessment, virtual classroom (Huang et al., 2021), and e-learning of students, mainly in engineering (Prahani et al., 2022). Nemorin et al. (2023) identify AI possibilities for niche market expansion. Ouyang and Jiao (2021) states that the AIED development trend supports the personalization of student learning, to lead to iterative development of personalized, data-driven and learner-centered learning. AI can help in identifying teaching tasks and teaching content accurately, where teaching strategies can be linked to learning profiles (Lin, 2022). AI can be applied to social networking sites and chatbots, expert systems for education, mentors and intelligent agents, machine learning, personalized educational systems, and virtual educational environments to develop professional competences (Tapalova and Zhiyenbayeva, 2022). AI presents potentials for education, but it is also important to consider related risks.

The risks when applying AI in education can span a wide spectrum. Debate and controversy have been generated among teaching communities and corporate AI giants (Al Braiki et al., 2020), where increased ethical risks (Lameras and Arnab, 2023) and bias are identified when using AI tools and techniques to model and inform instructional decisions and predict learning outcomes (Dieterle et al., 2022; Ibarra-Vazquez et al., 2023). Of note are concerns regarding personal data and learner autonomy (Nguyen et al., 2023), as well as in the governance of AI risk in human-centered education (Li and Gu, 2023). Risks are also related to equity, accountability, transparency, and ethics (Khosravi et al., 2022); as well as in the misuse of AI due to algorithm bias and lack of governance that inhibit human rights and lead to labor, gender, and racial inequality (Yang et al., 2021). Other risks include teacher labor automation and global platform infrastructures embedded in education (Rensfeldt and Rahm, 2023). The risks are important points for practical applications and must be addressed through educational research.

2.2 AIED educational research: progress and opportunities

Researching the potential of using AI in education can establish a link with pedagogical innovation processes and technological applications. Indeed, AI research in education has increased in recent years (Kaban, 2023; Vázquez-Parra et al., 2024b), with a high number of institutions and researchers with publications indicating a new trend for the artificial intelligence in education (AIED) community (Bittencourt et al., 2023). Chen et al. (2020) identified the main AI research topics as intelligent tutoring systems for special education; natural language processing for language teaching; educational robots for AI education; educational data mining for performance prediction; among others. AI, as a field of study, identifies innovations and resulting developments that have culminated in computers, machines and other artifacts with human-like intelligence, characterized by cognitive abilities, learning, adaptability, and decision-making capabilities (Chen et al., 2020; Ibarra-Vazquez et al., 2024). Practical applications include Benhadj et al. (2019) who integrated serious games into classroom management on a large scale, leading to improved discipline, motivation, and participation in the classroom. Also Andersen et al. (2022) used block-based programming in small groups to solve teacher-given tasks. Practical application research sheds light on knowledge transfer and it is also important to locate opportunities for further educational research.

The AIED research field presents opportunities to further increase its educational application possibilities. There is an urgent need for research and development in teacher preparation as well as in the philosophy of technology in education to bridge the gap between AI and education (Pham and Sampson, 2022). There are still doubts about the ability of AI to monitor students' behavior and direct learning, improve the efficiency of the education system, provide grades and reviews, reduce dependency on teachers, and improve social interaction (Al-Tkhayneh et al., 2023). For example, in the socioemotional domain of students, Lai et al. (2023) found that AI had a negative impact on adolescents' social adaptability, and that it is significantly negatively correlated with social adaptability and family support. In the same vein, Xie et al. (2022) highlight the need to target interventions according to the relationship between psychosocial factors and social adaptability to enhance the positive influence of AI and promote the development of social adaptability. Possibilities are located for systems to be implemented, models, standards, and invisible evaluations of learning (Rahm and Rahm-Skågeby, 2023). Opportunities increase when looking for studies on practical applications in communities in the Global South.

2.3 Science clubs: engines for scientific and complex thinking

Science clubs are educational settings where problem-solving is promoted through intentional, non-formal, school-based learning. In informal education, Burke (2023) analyzed STEM clubs to develop a community-responsive approach to out-of-school club programming. Larina et al. (2023) worked in the health field with student science clubs at a medical university to prepare students for future professional activities, locating motivational factors for learning. Similarly, Ilyenko et al. (2023) studied motivation with medical students participating in science clubs and found a high demand for the experience of research work, the expansion and deepening of knowledge in the specialty, as well as the positive impact of participation in science clubs on the further training of future clinicians. Sewry et al. (2023) also found positive attitudes from science club work that integrated kitchen chemistry practices, with improvements in conceptual understanding and improved student performance. Science clubs are presented as mobilisers of high ability thinking through challenging learning environments.

In this research, complex thinking is conceptualized as a cross-cutting macro-competency that encompasses four interrelated sub-competencies—systemic, critical, innovative, and scientific thinking. Together, these enable learners to address problems from diverse perspectives and develop integrated solutions to multifaceted, real-world issues (Sanabria-Z et al., 2024). Systemic thinking refers to the ability to recognize, model, and interpret the interconnections within complex systems (Cruz-Sandoval et al., 2023b). Critical thinking is understood as the capacity to challenge underlying assumptions, evaluate arguments, and examine evidence (Patiño et al., 2023). Innovative thinking denotes the ability to generate original and contextually appropriate solutions to problems (Suárez-Brito et al., 2024). Lastly, scientific thinking is defined as the process of posing hypotheses, designing empirical investigations, and interpreting findings to construct evidence-based knowledge (Cruz-Sandoval et al., 2023,a).

Training in scientific and complex thinking involves generating different and motivating scenarios. Their development in time might be influenced by different factors such as gender (Brage-del-Río et al., 2025; González-Gallego et al., 2025) For instance, Medina-Vidal et al. (2023) identified and substantiated the existence of a gender gap in the development of perceived complex thinking competency and its sub-competencies since women's perceived competency levels diminished as they progressed through their formative process. In the quest to develop scientific thinking and attract more individuals to science and technology studies, Lövheim (2014) worked with science clubs to make science more interesting and fun for students and to change young people's attitudes toward these topics. Also, Romaniuk et al. (2023) integrated science clubs and placed the development of medical students' research skills, systematization of information, and science communication. In the field of humanitarian sciences, Ermachkov et al. (2018) applied practices and methodological approaches in the organization of students' scientific activities, aiming to improve the quality of students' scientific research. Buenestado-Fernández et al. (2023) analyzed participants in science clubs in Mexico and found that science education activities with a gender perspective are necessary in non-formal education spaces such as science clubs.

Building on these insights, the inclusion of gender as an analytical lens in this study is grounded in evidence documenting persistent differences between men and women in STEM participation and competency development. Social and cultural factors, such as gender stereotypes linked to technical skills, unequal access to role models or mentors, and societal expectations regarding career paths, can shape both engagement and self-perception in STEM learning environments (Hernández-Pérez et al., 2024; Beroíza-Valenzuela and Salas-Guzmán, 2024). In non-formal contexts such as science clubs, prevailing norms may favor male participation, for example by framing activities around tools traditionally coded as masculine or through competitive formats that may limit female engagement. The literature identifies strategies to foster more inclusive environments, including the design of collaborative projects with real-world applications, balanced representation among facilitators, and the explicit discussion of gender bias during activities (Archer et al., 2025). Furthermore, Beroíza-Valenzuela and Salas-Guzmán (2024) highlight that educational resources, cultural norms, and institutional support mechanisms play a decisive role in reinforcing or reducing gender gaps in STEM engagement. Considering that science clubs are central to fostering both scientific and complex thinking competencies, integrating a gender perspective enables us to examine how inclusivity—or its absence—may influence the development of these competencies across diverse student populations. From this perspective, how can innovative spaces are encouraged in science clubs that work with AIEDs that promote high capacities?

3 Methodology

3.1 Research design

This study employed the multiple case study methodology (Yin, 1993) to examine at an individual and collective level the development of complex thinking and scientific thinking among 83 students participating in AI-themed science club activities. A case study can be defined as an integrated and bounded system, emphasizing its nature as an object rather than a process (Stake, 2007). It entails a specific and intricately operational entity that can encompass individuals, institutions, characteristics, and interrelationships (Yin, 2006). In the context of this study, a case includes a unique configuration of students, mentors, technologies, and pedagogical strategies within each club. The rationale for selecting science clubs as the unit of analysis lies in their hybrid nature: they combine project-based, exploratory, and interdisciplinary learning, making them ideal micro-environments for studying how learners engage with abstract and complex domains such as AI.

In this study, each science club is considered a bounded case comprising a specific configuration of students, mentors, AI tools, thematic focus, and pedagogical strategies. While the present analysis focuses primarily on quantitative data derived from standardized instruments, the case study framing is grounded in the recognition that each club operates within a unique educational micro-context. These contextual differences—including thematic variation, participant composition, and implementation setting—inform the comparative interpretation of results. The multiple case study approach thus enables the identification of patterns across diverse contexts while preserving the integrity of each case as a distinct analytical unit. We acknowledge that this iteration of the research does not incorporate qualitative coding or ethnographic elements; however, rich contextual descriptions and standardized cross-site protocols provide the comparative depth characteristic of multi-case designs. Future work will integrate interviews, open-ended responses, and observational field notes to further align methodological practice with a fully mixed-methods multiple case study approach.

The comparative dimension of the study was carefully designed to allow for both cross-case analysis and contextual sensitivity. While students in each club engaged in different AI-themed projects, all were guided by a shared pedagogical structure emphasizing problem-solving, creative design, and collaborative exploration. The thematic variation across clubs was not a limitation but a feature: it enabled a richer understanding of how students activate scientific and complex thinking in diverse yet comparable educational contexts.

Each science club integrated hands-on, project-based activities directly related to the thematic focus and AI tools under study. For example, in "Artificial Intelligence Applications: Data Science for Maternal Health and Cancer Care" (OAX5), students learned data analysis in R and ArcGIS, applying geospatial methods to explore environmental determinants of health. In "AI-Powered Drug Discovery" (GTO2), participants worked with computational models to identify potential new uses for existing drugs. "Bits and Atoms: Quantum Computing and Machine Learning" (MTY3) provided an introduction to quantum computing concepts alongside practical machine learning exercises, while "Sensory Expansion" (MTY5) focused on programming algorithms to detect luminescent properties of materials for diagnostic purposes. In "Adventures in AI" (GDL1), students explored everyday applications of machine learning, including self-driving laboratory simulations, and in "Untangling the Neurons of Artificial Intelligence" (GDL2) they designed and trained artificial neural networks inspired by brain processes. These case-specific activities illustrate the diversity of contexts in which students engaged with AI concepts and developed higher-order thinking skills.

3.2 Research questions

The present study was guided by four research questions aimed at understanding how students engage with complex and scientific thinking through their participation in AI-focused science clubs. The participant group consisted of 83 students-—42 women and 41 men—enrolled in six AI-themed clubs implemented in four different Mexican cities. These clubs provided a range of thematic areas, such as computing, medicine, and robotics, allowing for an exploration of potential variations in the development of competencies across contexts. Specifically, the study sought to explore:

> RQ1) How students perceive the development of their complex thinking competencies because of participating in practical educational applications of AI.
> RQ2) How students perceive the development of their scientific thinking competencies under the same conditions.
> RQ3) Whether differences exist in these perceptions across distinct thematic areas of AI within the clubs, such as computing, medicine, and robotics.
> RQ4) Whether gender-related patterns emerge in students' self-perceptions of these competencies.

These questions were addressed through a multiple case study design, which allowed for in-depth analysis of both individual experiences and contextual variations across six different science clubs. By focusing on these dimensions, the study aimed to generate insights into how informal, project-based learning environments can foster key transversal competencies in diverse student populations.

3.3 Data collection

Prior to any data collection activities, the entirety of science club participants enrolled in AI-themed clubs were invited to participate in the study and were provided with detailed information about the nature of the research, its potential impact, and the intended use of the collected data. Participants were explicitly informed about their voluntary participation and were assured of the confidentiality and anonymity of their responses. While all the science club participants took part in the club activities, this study presents results of 83 high school and university students having consented to participate in the study distributed in six groups or cases. This collection of cases, each representing a unique and complex phenomenon with practical educational applications of AI, has been analyzed to identify the scientific skills and complex thinking competency of the participants. Each group or case was presented with a series of learning activities including a game-base activity and a questionnaire to collect data regarding their complex thinking competency.

Data collection was semi-simultaneous, involving the participation of a team of six trained researchers and research assistants. The participant recruitment process began with obtaining formal permission from the coordinators of each science club to invite both participants and instructors to join the study. Once approval was granted, instructors were contacted via e-mail and invited to an online briefing session where the research objectives, data collection instruments, and participant activities were presented in detail, following the main points of the research protocol. Recruitment of club participants took place at the onset of the club activities, with invitations extended directly during the first session. To ensure methodological consistency across sites, the research team co-designed a standardized protocol and held virtual coordination meetings prior to fieldwork to align procedures, ensuring that the same instruments were applied in the same order and manner in each location. This distributed data collection structure was necessary due to the clubs being held concurrently across different cities (i.e., Guadalajara, Monterrey, Oaxaca, and Guanajuato) and separate locations within the city. While data collection did not occur at the exact same time in all four cities, it occurred during the same time span, which made it impossible for the same researchers to be in-person in all groups. Despite the logistical complexity, a consistent protocol was used to ensure coherence in data gathering. In each case, students interacted with AI content under similar pedagogical conditions, enabling comparisons while respecting the integrity of each unique context. In this sense, the analyzed cases serve as microcosms, allowing for an in-depth exploration of their unique contexts and the development of their activities. Thus, the comparability of the cases is grounded in their shared structure and theoretical alignment, while the value of the comparison lies in highlighting how varied educational contexts mediate students' engagement with AI and the development of higher-order thinking skills. Table 1 presents the science club name and the description of the covered thematic areas, the utilized technologies, and sociodemographic data to describe the participants.

3.4 E-complexity instrument

E-Complexity is a Likert-scale questionnaire developed to assess students' perception of their development in the complex thinking competency and its four sub-competencies: critical thinking, scientific thinking, innovative thinking, and systemic thinking (Sotelo et al., 2023). The instrument consists of 25 items rated on a five-point Likert scale, ranging from "Strongly disagree" (1) to "Strongly agree" (5). E-Complexity was designed through a comprehensive three-stage validation process, including theoretical, design, and content validation by subject-matter experts. A theoretical review of existing instruments revealed the need for a more integrative tool focused specifically on the structure of complex thinking. Additionally, the instrument has undergone rigorous statistical validation (Cruz-Sandoval et al., 2023). Its internal consistency, evaluated using Cronbach's alpha, achieved a coefficient of 0.93, indicating excellent reliability across its items (Vázquez-Parra et al., 2024a). Furthermore, Vázquez-Parra et al. (2024b) confirmed its construct validity through confirmatory

TABLE 1 Description of the study cases.

Case	Title and description	Participants		
		Women	Men	Total
OAX5	Artificial intelligence applications: data science for maternal health and cancer care. Students learn data science fundamentals in R and ArcGIS and apply them to fetal and oncological programming. Geospatial analysis is used to understand data patterns and environmental determinants affecting health.	6	9	15
GTO2	AI-powered drug discovery: bringing Old Drugs Back to Life. This club explores strategies for discovering new uses for existing drugs in the market, harnessing the power of computers to revolutionize drug repurposing and production.	13	2	15
MTY3	Bits and atoms: quantum Computing and Machine Learning. This club offers an immersive journey into the realm of computing, with a specific focus on the groundbreaking field of quantum computing. Participants delve into the foundational concepts of computing while also venturing into the cutting-edge world of quantum computation.	3	13	16
MTY5	Sensory expansion: perceiving Through Technology. In this club, participants learn how to harness technology to perceive and visualize the optical characteristics of materials possessing unique optical and electronic properties that play a pivotal role in disease diagnosis and detection. In addition, they delve into the world of programming to develop algorithms that can identify a material's luminescent properties based on its color.	6	4	10
GDL1	Adventures in AI: exploring uses for machine learning in everyday life and self-driving laboratories. Participants delve into AI fundamentals, coding in Python, practical AI applications with ChatGPT, and its role in chemical research and self-learning robots.	5	7	12
GDL2	Untangling the Neurons of Artificial Intelligence. This club explores the workings of AI, focusing on computational models inspired by the brain's neural networks. Participants learn about natural language processing tools and build and train their own neural networks.	9	6	15
Total		**42**	**41**	**83**

Source: own elaboration. The bold values indicate total number of participants.

factor analysis within a structural equation modeling framework, which supported the theoretical four-subcompetency structure and reinforced the instrument's credibility for measuring these latent constructs.

3.5 Data analysis

The analytical framework of qualitative multiple case studies often extend to include descriptive statistics analysis. This statistical

TABLE 2 Complex thinking competency and sub-competencies.

Code	Statistic	Complex thinking	Systemic thinking	Scientific thinking	Critical thinking	Innovative thinking
Overall	Mean	4.11	4.18	4.06	4.12	4.08
	Sd	0.55	0.45	0.69	0.46	0.56
GDL1	Mean	4.24*	4.31*	4.14	4.31*	4.21*
	Sd	0.67	0.61	1.06	0.44	0.47
GDL2	Mean	4.12	4.18	4.20*	4.12	3.98
	Sd	0.48	0.38	0.58	0.43	0.50
GTO2	Mean	4.15	4.28	4.18	4.09	4.05
	Sd	0.52	0.42	0.54	0.53	0.61
MTY3	Mean	4.09	4.13	3.94	4.17	4.11
	Sd	0.62	0.53	0.83	0.50	0.61
MTY5	Mean	4.08	4.05	3.98	4.13	4.15
	Sd	0.49	0.45	0.64	0.38	0.53
OAX5	Mean	4.00	4.12	3.94	3.94	4.00
	Sd	0.47	0.34	0.40	0.45	0.67

Means and standard deviations. ∗ Highest mean per competency.

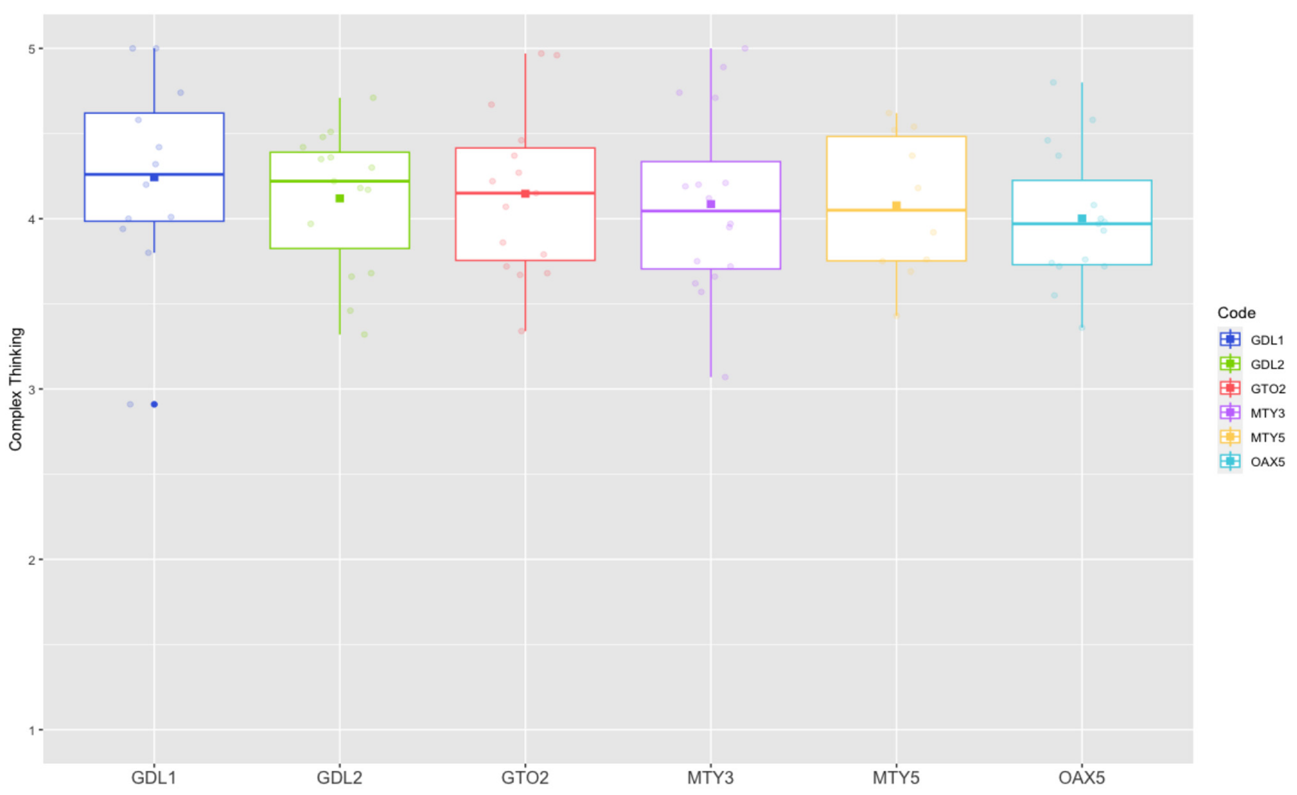

FIGURE 1
Complex thinking competency by case.

dimension serves as a complementary tool to summarize and present key characteristics and trends within and across cases. While qualitative in nature, this incorporation of descriptive statistics offers a quantitative lens through which patterns, variations, and emergent themes can be elucidated, adding a layer of empirical rigor to the comprehensive qualitative analysis. In this multiple case-study research, descriptive statistical analyses were performed using the R software and RStudio. We emphasized measures of central tendency, specifically the mean and standard deviation. To enrich our research, we also employed tools such as Boxplots, Principal Component Analysis (PCA), Biplot visualization, ANOVA, and the t-test.

The Boxplot, or whisker diagram, graphically displays data distribution by quartiles, emphasizing its spread, symmetry, and potential outliers. PCA, on the other hand, is a dimensionality reduction technique that converts a set of correlated variables into uncorrelated principal components. The first of these components captures the most variability in the data, followed by the second, and so on. This analysis is visualized with the Biplot, projecting both observations and variables onto a plane defined by the principal components. ANOVA analysis is used to evaluate differences between the means of three or more groups, determining if these variations are statistically significant. Lastly, the t-test allows us to determine if there are significant differences between the means of the cases. All analyses were conducted in R version 4.5.1 (2025-06-13) and RStudio version 2025.5.1.513 ("Mariposa Orchid"), using the following packages: dslabs, dbplyr, tidyverse, ggplot2, devtools, and ggbiplot.

4 Results

The objective of this study was to investigate how participation in science clubs focused on AI-related projects supports the development of complex thinking and scientific thinking among high school and university students.

In response to RQ1, we first identified the levels of complex thinking competency among students actively engaged in practical educational applications of AI in science clubs. Table 2 displays the results regarding students' perceptions of complex thinking competency, including the mean values and standard deviation for each of its sub-competencies, segmented by code corresponding to each case study.

As observed in Table 2, students who perceive the highest development in complex thinking competency belong to the group coded as GDL1 Adventures in AI: exploring uses for machine learning in everyday life and self-driving laboratories, where the simulation game "Lost" was applied, achieving an average of 4.24. In terms of sub-competencies, GDL1 also leads in systemic thinking (4.31), critical thinking (4.31), and innovative thinking (4.21). However, for the scientific thinking sub-competency, it's the GDL2 group Untangling the Neurons of Artificial Intelligence that obtained the highest score with a mean value of 4.20. On the opposite end, the OAX5 group Artificial Intelligence applications: data science for maternal health and cancer care, which utilized "Save the planet," is highlighted for having the lowest perceived development in the complex thinking competency with an average score of four. Regarding systemic thinking, the MTY5 group

TABLE 3 ANOVA results for the perception of complex thinking competency across groups.

Df	Sum Sq	Mean Sq	*F-value*	Pr (>F)
5	0.432	0.08	0.037	0.862

Sensory Expansion: Perceiving Through Technology presents the lowest development in this sub-competency. For scientific thinking, both MTY3 Bits and Atoms: Quantum Computing and Machine Learning and OAX5 have the lowest perception with an average score of 3.94. The OAX5 group also displays the lowest perception in critical thinking with a score of 3.94. Finally, for the innovative thinking sub-competency, the GDL2 group presents the lowest perception with a mean value of 3.98.

The mean represents the central value of a dataset, while the standard deviation reveals the spread of these values around that mean. A small deviation value indicates data concentration around the mean, and a large one denotes dispersion. Figure 1 illustrates the dispersion of the average values related to the perception of complex thinking competency for each group. It is highlighted that GDL1 and MTY3 display outlier values in the lower quartile in relation to the perceived development of this competency. It's notable that all groups perceive a level of development in complex thinking with an average of four or higher. Particularly outstanding are GDL1 with 4.24, GTO2 with 4.15, and GDL2 with 4.12, all surpassing an average value of 4.10. On the other hand, MTY3 with 4.09, MTY5 with 4.08, and OAX5 with 4.0 present average values exceeding four.

In relation to RQ3, Table 3 presents the ANOVA analysis of the average values corresponding to the groups' perception in the development of complex thinking competency. With a 95% confidence level (*p-value* $= 0.05$), the results indicate that there are no statistically significant differences between the groups (*p-value* $= 0.862$).

Figure 2 illustrates the dispersion in the perception among various groups concerning the development of the sub-competencies of complex thinking. It's noteworthy that in the sub-competencies of innovative thinking and scientific thinking, there are more outlier values, as well as a concentration of average values in the lower quartile. This might suggest that a larger number of students perceive themselves as having limited development in these sub-competencies.

Regarding the principal component analysis, in response to RQ1, Table 4 indicates that the first principal component (PC1) combined with the second principal component (PC2) together account for 86% of the variance in the original data: PC1 contributes 75% and PC2 adds 11%. Furthermore, the 0.52 coefficient for systemic thinking suggests a positive relationship with PC1. Similarly, the 0.68 coefficient shows that innovative thinking is positively associated with PC2. In this context, PC1 reflects the students' perception of their ability to understand interrelations among various parts of a system and to find holistic solutions. On the other hand, PC2 represents the students' capacity to devise creative and novel solutions to problems.

To analyze the behavior of the students by group and avoid issues of collinearity, we conducted a Biplot of form, which

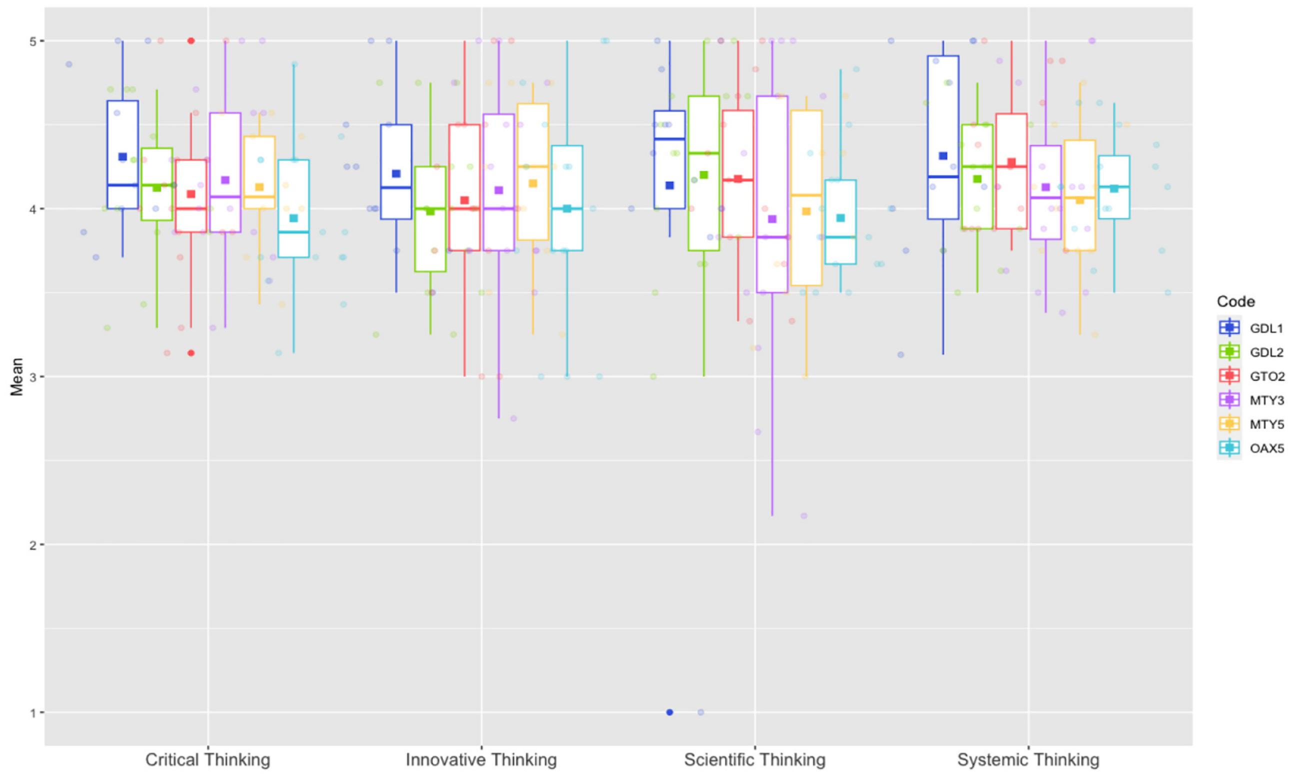

FIGURE 2
Complex thinking sub-competencies by case.

TABLE 4 Principal component matrix.

Concept	PC1	PC2	PC3	PC4
Systemic thinking	0.52	−0.29	0.32	0.72
Scientific thinking	0.48	−0.61	−0.48	−0.38
Critical thinking	0.51	0.25	0.61	−0.54
Innovative thinking	0.47	0.68	−0.52	0.17
Standard deviation	1.73	0.68	0.58	0.41
Proportion of variance	0.75	0.11	0.08	0.04
Cumulative proportion	0.75	0.86	0.94	1.00

enhances the visualization of individual observations (see Figure 3). In relation to RQ3, students have been coded according to the group they belong to. Although the analysis results do not provide a clear pattern or trend regarding students' perception of their development in the sub-competencies, it's noteworthy that students from the GDL2 group perceive themselves as having a more advanced development in scientific, systemic, critical, and innovative thinking. On the other hand, there's a student from GDL1 who appears to perceive little to no development across all sub-competencies. Regarding the development of critical thinking, two students from GTO2, two from MTY3, and one from OAX5 stand out.

In response to RQ4, Figure 4 presents an analysis of students' perceptions regarding their proficiency in complex thinking, segmented by both gender and group. Notably, women, on average, exhibit a slightly elevated perception of their development in complex thinking with a mean score of 4.13, compared to their male counterparts who averaged 4.09. Within the specific groups, women from GDL1, GTO2, and OAX5 exhibited the highest mean perceptions with scores of 4.29, 4.18, and 4.14 respectively. Conversely, men from GDL2, MTY3, and MTY5 displayed higher mean scores of 4.21, 4.10, and 4.21 in that order. Figure 4 displays the dispersion of male and female students concerning their perception of complex thinking development by group.

A t-test analysis was conducted to determine if there are significant differences between men and women from each group regarding the competency of complex thinking. With a significance *p-value* of 0.05, the results indicate that there are no statistically significant differences in the perception of complex thinking development between men and women (see Table 5).

In response to RQ2, a similar analysis was undertaken, focusing on the sub-competency of scientific thinking among men and women participants across the different groups (see Figure 5). Overall, women perceive themselves to exhibit a higher degree of scientific thinking, with an average rating of 4.13, whereas men reported an average of 4. Specifically, women from the GDL1, GTO2, and OAX5 groups rated their proficiency in this sub-competency higher, with mean scores of 4.33, 4.27, and 4 respectively. Conversely, men from the GDL2, MTY3, and MTY5 groups perceived their proficiency in scientific thinking to be

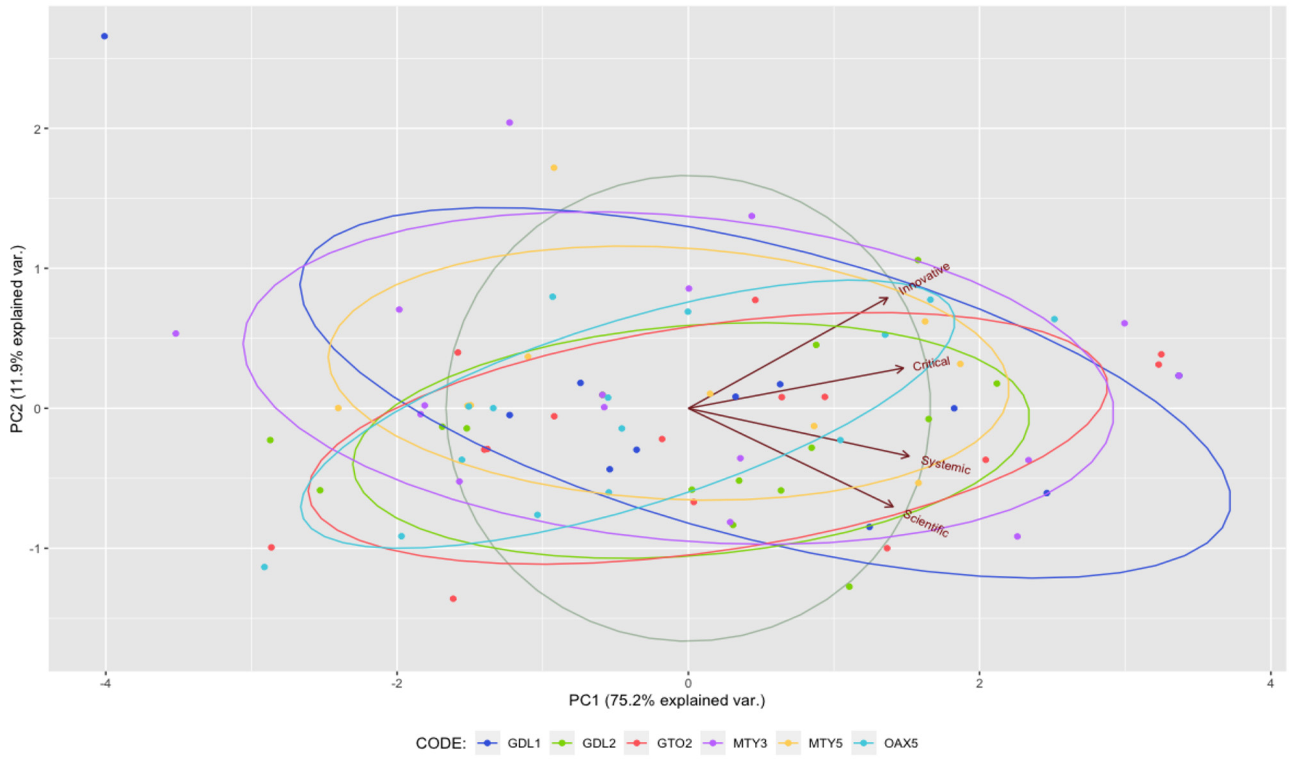

FIGURE 3
Biplot. Biplot of shape ($\alpha = 1$).

more pronounced, recording average scores of 4.31, 3.97, and 4.04 respectively.

Figure 5 depicts the variability in the perception of scientific thinking sub-competency among men and women of the different groups. Notably, the behavior of the men in group MTY3 stands out; the data reveals significant dispersion with a pronounced presence of outlier values in this group.

Table 6 presents the t-test analysis conducted to determine whether there are significant differences in the perception of the development of the scientific thinking sub-competency between men and women in the groups. Using a significance level of *p-value* at 0.05, the results indicate that there are no statistically significant differences between men and women in the different groups.

Finally, in relation to RQ3, we conducted an ANOVA analysis to determine if there are significant differences among the groups concerning their perception in the development of the scientific thinking sub-competency. Using a significance level with a *p-value* of 0.05, the results indicate that there are no statistically significant differences in the perception of this sub-competency among the groups (see Table 7).

5 Discussion

All cases exhibit a perceived level of development in complex thinking, averaging four or higher. As shown in Figure 1, three groups focusing on the practical application of AI in computing and medicine surpassed an average value of 4.10, while the other three surpassed an average of 4. However, it is important to interpret these trends carefully, as statistical analyses did not identify significant distinctions among groups or genders. Although some variations were observed, statistical analyses did not reveal any significant differences between groups ($p > 0.05$). Consequently, any reference to differences in mean values throughout this discussion refers strictly to descriptive trends rather than statistically significant effects. These trends are interpreted with caution, focusing on observed patterns and their potential practical implications, rather than asserting definitive causal relationships.

This perspective aligns with the insights of Romaniuk et al. (2023), who integrated science clubs into medical education, emphasizing the development of research skills and science communication. Their emphasis on these elements resonates with our findings and underscores the broader significance of cultivating complex thinking in educational contexts. While our findings echo the importance of fostering complex thinking across various participant groups, the absence of statistically significant differences suggests that the development in this domain may be more universally distributed among the studied cohorts. This implies that interventions aimed at enhancing complex thinking skills may benefit diverse educational settings, irrespective of the specific technological approach employed.

Drawing parallels with Larina et al. (2023) and Ilyenko et al. (2023), who emphasized the positive impact of science clubs on the development of medical students, our findings contribute to the broader discourse on the role of science clubs in shaping

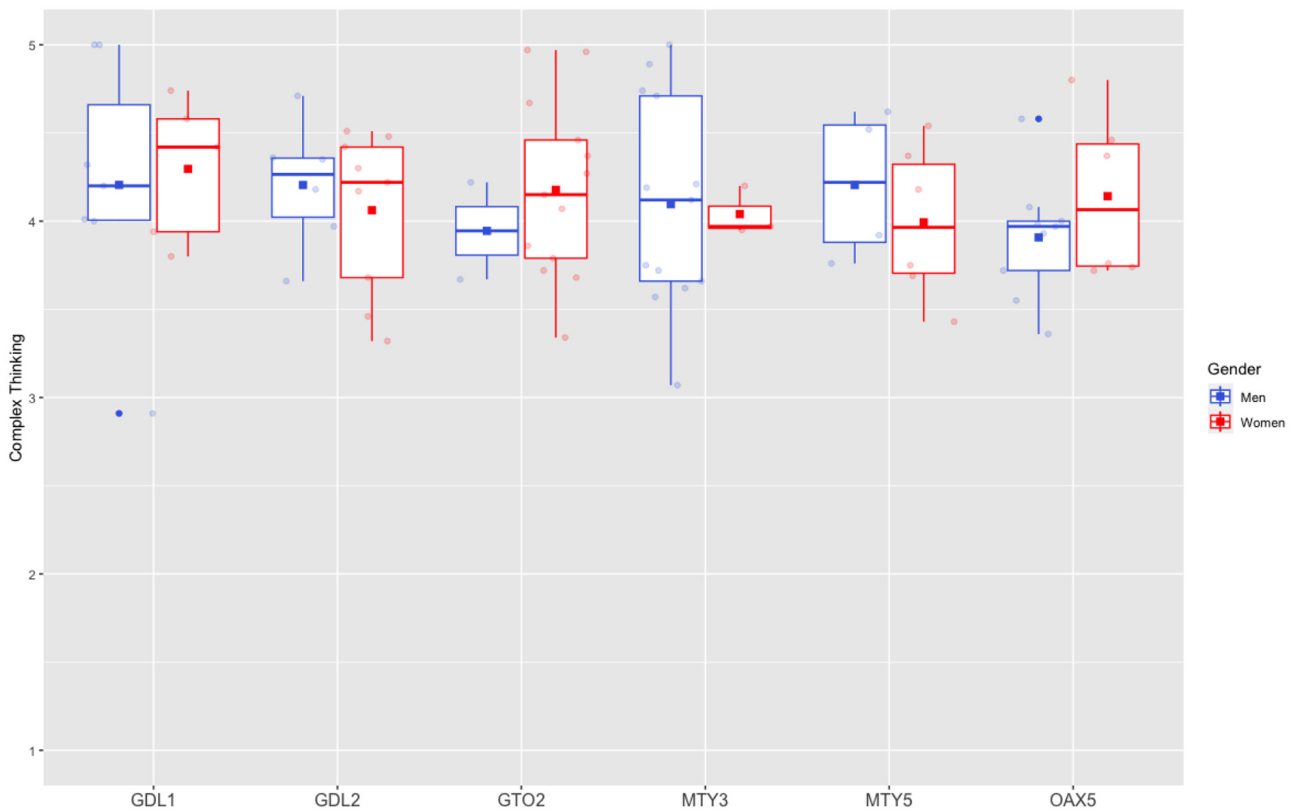

FIGURE 4
Complex thinking sub-competencies by gender. Boxplot.

TABLE 5 Complex thinking.

Women vs. Men	*t*	df	*p-value*
GDL1	−0.26	9.70	0.79
GDL2	0.67	12.45	0.51
GTO2	−0.76	1.58	0.54
MTY3	0.30	13.80	0.76
MTY5	0.76	6.62	0.47
OAX5	−1.05	8.67	0.31

T-test. Significant differences between mean values in the perception of complex thinking of women and men by code.

the cognitive skills of participants. These results prompt further exploration into the nuanced factors influencing the perceived development of complex thinking in distinct educational contexts and underscore the need for continued research and practical interventions to optimize the cultivation of this crucial cognitive skill in medical education and beyond.

Beyond group-level comparisons, gender-based patterns also emerged, though these too lacked statistical significance. On average, women reported slightly higher perceived development in complex thinking (mean = 4.13) compared to men (mean = 4.09); however, this difference was not statistically significant ($p > 0.05$).

This non-significant trend is consistent with previous findings by Medina-Vidal et al. (2023), who identified a gender gap in the perceived achievement of complex thinking competency among students, where women initially surpassed their male peers in most competencies, but their perception diminished as they progressed academically. While the magnitude of the difference in our study is small and not statistically supported, it prompts consideration of gender-specific factors that might influence the perception of complex thinking. Any interpretation of this tendency should be framed as exploratory, and future research should investigate whether such patterns persist in larger, more diverse samples.

Similarly, women self-reported higher levels of scientific thinking (mean = 4.13) compared to men (mean = 4.00), yet this difference was also not statistically significant ($p > 0.05$). As with complex thinking, these results reflect descriptive tendencies rather than confirmed differences. This finding complements the work of Medina-Vidal et al. (2023), which documented gender-based variations in cognitive skills, but in the present study such variations cannot be considered statistically reliable. Despite the absence of statistical significance, these descriptive trends raise relevant questions about potential factors—social, cultural, or educational—that could influence students' self-perceptions of scientific thinking. The implications for educational practice lie in fostering an inclusive environment that encourages positive self-perceptions of scientific abilities in all learners, without assuming inherent differences between genders.

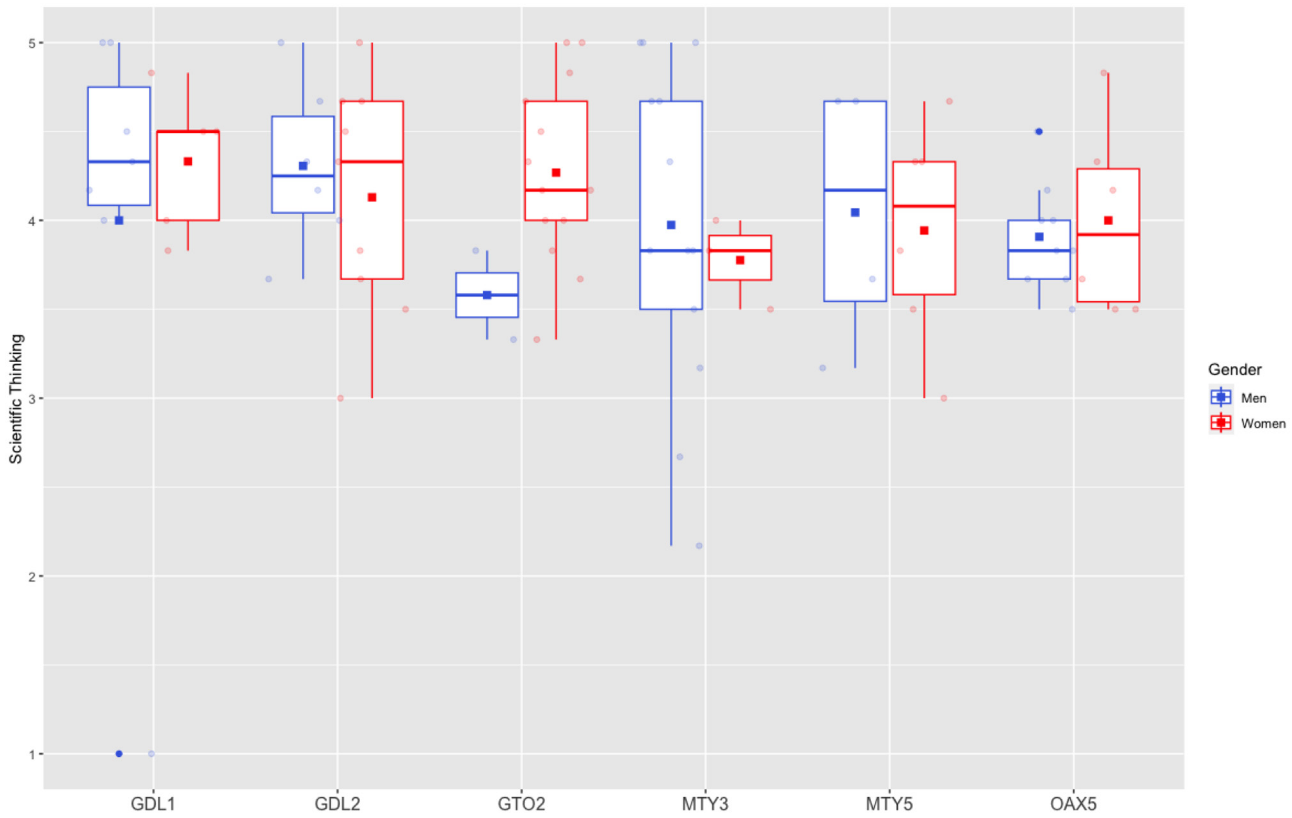

FIGURE 5
Scientific thinking by gender. Boxplot.

One notable limitation of this study is its reliance on self-reported data, which can be affected by over- or underestimation of one's competencies. While self-perception measures are valuable for capturing students' subjective experiences, they do not always align with actual performance, potentially leading to discrepancies between perceived and demonstrated competence. Future research should integrate self-reports with qualitative evidence (e.g., interviews, reflective journals) and objective performance measures (e.g., standardized tests, applied tasks) to triangulate results and provide a more accurate, comprehensive, and validated understanding of how complex and scientific thinking competencies develop.

TABLE 6 Scientific thinking.

Women vs. Men	*t*	df	*p-value*
GDL1	−0.60	7.39	0.56
GDL2	0.59	12.84	0.55
GTO2	−2.38	1.74	0.15
MTY3	0.66	12.81	0.51
MTY5	0.21	5.56	0.83
OAX5	−0.38	7.12	0.71

T-test. Significant differences between mean values in the perception of complex thinking of women and men by code.

TABLE 7 Scientific thinking.

Df	Sum Sq	Mean Sq	*F-value*	Pr (>F)
5	1.07	0.21	0.44	0.819

Analysis of significant differences between mean values in perceived achieve-ment between codes (ANOVA).

6 Conclusions

The study aimed to investigate the perceived development of complex thinking and scientific thinking among participants engaged in practical educational applications of AI within science clubs. The findings reveal that (a) participants in all cases of practical applications of AI demonstrated a high perceived level of development in complex thinking, with three groups focused on AI applications in computing and medicine surpassing the others; (b) although no statistically significant differences were found, women, on average, tended to report slightly higher perceptions of complex thinking development compared to their male counterparts; and (c) a similar non-significant trend was observed for scientific thinking, with women reporting marginally higher self-perceived levels than men. These gender-related observations should be interpreted as descriptive tendencies rather than statistically confirmed differences.

While the multiple case study methodology employed in this research project offers valuable insights into the experiences of students participating in science club activities focused on practical applications of AI, there are notable limitations to consider. Firstly, the study's scope is limited to a specific cultural context, focusing on science clubs within the Mexican community. This may restrict the generalizability of findings to broader cultural or geographical settings, as educational practices and perceptions of AI may vary across different communities and regions. Secondly, self-reported measures might not fully capture the nuanced aspects of complex thinking and scientific skills, relying on participants' subjective interpretations. Furthermore, the study's quantitative dimension, while providing valuable statistical insights, may not fully capture the richness and depth of qualitative nuances within each case. The complexity of human experiences and the multifaceted nature of educational interventions might not be entirely represented through descriptive statistics alone.

Despite these limitations, the study offers valuable insights into the practical educational applications of AI in science clubs, with findings that can inform future research and guide educational interventions in similar contexts. By showing how AI-centered extracurricular initiatives can foster higher-order thinking skills, this work provides actionable guidance for educators, policymakers, and program designers on integrating emerging technologies into inclusive and equitable educational strategies.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by Writing Lab, Institute for the Future of Education, Tecnologico de Monterrey, Mexico. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

MR-M: Validation, Writing – original draft, Conceptualization, Supervision, Project administration, Resources, Investigation, Formal analysis, Writing – review & editing, Funding acquisition. AP: Writing – review & editing, Validation, Formal analysis, Supervision, Investigation, Writing – original draft, Conceptualization. MC-S: Investigation, Supervision, Conceptualization, Writing – review & editing, Software, Data curation, Visualization, Writing – original draft, Validation, Methodology, Formal analysis.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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