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The role of generative AI in collaborative problem-solving of authentic challenges

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Abstract

This study investigates undergraduate and postgraduate teamwork in a four-week 'Generative AI for Social Good' hackathon, focusing on how students use GAI tools in authentic problem-solving within their learning ecology. It examines the factors that foster productive collaboration and explores evidence of AI extending human cognition beyond mere tool use. Data sources included pre- and post-surveys, interim reports, submitted artefacts and team workspace logs. Generative AI (GAI) use accounted for nearly half of the demonstrated digital competence instances—particularly in content creation and problem-solving—highlighting its role in facilitating collaborative, inquiry-driven learning. Findings reveal that success depended not on computational expertise, but on shared values, diverse skill sets, effective team structures and clear communication. GAI's role evolved with teams' technical backgrounds, dynamically supporting collaborative knowledge building and moving beyond instrumental use to actively shape emerging knowledge building. These insights offer valuable implications for the pedagogical design of learning with and through GAI.

KEYWORDS

digital competence, generative artificial intelligence, hackathon, human–AI collaboration, knowledge building

Practitioner notes

What is already known about this topic

- Generative Artificial Intelligence (GAI) has the potential to support personalized learning, content creation and problem-solving in educational contexts.
- Collaborative problem-solving (CPS) benefits from digital literacy and the ability to leverage technologies for co-construction of knowledge, particularly in addressing authentic, real-world challenges.
- AI literacy is increasingly seen as an important aspect of digital competence, but there is no empirically supported consensus on what competencies should be prioritized.

What this paper adds

- Hackathons (and by extension other authentic collaborative inquiry settings) provide opportunities for extending human intelligence through human–AI interactions in coupled human–AI hybrid systems that support knowledge building to address real-world challenges.
- GAI can be leveraged to support humans for ideation, content generation, prototyping, communication, etc. in collaborative knowledge building settings.
- GAI's role varies depending on the team's technological expertise, with less experienced teams using it for self-directed learning and creative support, while advanced teams use it for automation and technological innovation.
- Success is not fully determined by technological expertise but by effective collaboration (eg, shared project values, diverse expertise, effective communication).

Implications for practice and/or policy

- Incorporate GAI into interdisciplinary collaborative learning opportunities that foster knowledge co-creation and team building.
- Focus on building GAI-related digital competencies through promoting collaboration, communication and problem-solving beyond a narrow technocentric focus.
- Adopt project-based approaches such as Hackathons that prioritize student agency in the orchestration of AI and human interactions that extend human cognition.
- Establish guidelines for collaborative use and ethical adoption of GAI in educational settings.

INTRODUCTION

Recent developments in GAI show great promise in education—from student-facing tools like intelligent tutoring systems, chatbots and simulations to teacher-focused applications that auto-generate lessons and assessments, easing teachers' workloads (Rodriguez-Torrealba et al., 2022). Studies also show ChatGPT can facilitate brainstorming, summarizing and problem-solving, improving writing, creativity and critical thinking (AlAfnan et al., 2023; Urban et al., 2024); though it may also enable academic misconduct (Stokel-Walker, 2022).

Most prior work treats AI as a mere tool or human-intelligence analogue (Rismanchian & Doroudi, 2023), which limits our vision of close human–AI collaboration. Cukurova (2024) instead frames hybrid intelligence as an extension of human cognition, calling for research on how AI and human intelligence can complement each other in socio-technological ecosystems (Dellermann et al., 2019) beyond structured classroom settings with predetermined learning objectives and close-ended activities.

This study explores GAI's role in collaborative, creative knowledge building around authentic social challenges. We position GAI not just as a source of prepackaged solutions but as a co-creator in ideation and cross-disciplinary synthesis (Scardamalia, 2002), embodying Cukurova's view of tightly coupled human–AI systems. We also examine how digital competencies enable—and sometimes constrain—collaborative knowledge construction when mediated by GAI and other tools, treating digital skills as foundational to evolving knowledge building communities.

We selected a non-credit bearing hackathon open for cross-campus voluntary participation by undergraduate and postgraduate students at a publicly funded Hong Kong university as our study context as its flexible design is free from curricular or assessment constraints (Briscoe & Mulligan, 2014). Hackathons are time-limited events where programmers, coordinators and designers collaborate on software solutions, blending competition, teamwork and learning. They build networks, foster interdisciplinary problem-solving, raise social-issue awareness and develop technical skills (Briscoe & Mulligan, 2014; Cobham et al., 2017) and have been applied educationally to tackle real-world challenges (Lyons et al., 2021). This setting gives students autonomy to self-organize and innovate in a tech-rich environment where GAI tools support authentic problem-solving (Wang, et al., 2018). By requiring interdisciplinary teams, we can examine how team composition and dynamics interact with digital competence and GAI use during collaborative knowledge building.

LITERATURE REVIEW

While emerging technologies like AI often lead to calls for new forms of 'literacy' (eg, Long & Magerko, 2020), we argue that it is more effective educationally to view the skills needed to use AI within a broader digital competence framework. Rather than focusing solely on acquiring new digital skills, we examine how GAI use interacts with knowledge building processes and the digital competencies involved. This literature review outlines our conceptualization of AI literacy as part of digital competence and collaborative knowledge building in interdisciplinary teams.

Digital competence and AI literacy

With the rise of AI, especially GAI, the concept of AI literacy has appeared in research spanning education, the workforce and lifelong learning (Almatrafi et al., 2024), often emphasizing technical skills from basic understanding to advanced application development. A review of AI literacy in higher and adult education (Laupichler et al., 2022) found significant variations in focus—some studies highlight programming, while others stress reflective and evaluative abilities, though there is some overlap in the core competencies highlighted. Instead of a technocentric approach, we consider the European Digital Competence Framework (DigComp 2.2; Vuorikari et al., 2022) a more suitable model for defining the skills needed to use AI or GAI effectively in real-world problem-solving. Developed through rigorous research, DigComp 2.2 identifies key aspects of digital competence essential for individual and societal well-being and groups them into five competence areas. AI, as a 'new and emerging technology', is relevant to all five areas: information and data literacy, communication and collaboration, digital content creation, safety and problem-solving.

Information and Data Literacy (IDL) involves finding, evaluating and managing data, information and digital content. While GAI can efficiently search and summarize research, IDL skills—such as triangulating with search engines and assessing source credibility—are essential for detecting AI hallucinations and validating outputs.

Communication and Collaboration (C&C) refers to interacting, sharing, collaborating and engaging in citizenship rights and responsibilities through digital technologies. AI tools can facilitate meeting coordination, draft minutes and support communication among team members.

Digital Content Creation (DCC) refers to developing, integrating and reworking digital content. Programming languages and GAI authoring tools are widely used for creating various content types. Intellectual property rights related to GAI use must be considered alongside traditional copyright and licensing standards.

Safety pertains to protecting physical, virtual, mental and environmental well-being in digital contexts. AI introduces new dimensions and challenges to digital safety concerns.

Problem-solving (PS) involves identifying and resolving technical issues, as well as creatively using digital tools to innovate. This competence includes analysing problems and understanding how to use specific tools—such as programming languages versus AI applications—to achieve desired outcomes.

While DigComp has been found to be a popular framework adopted in digital competence research in higher education, the knowledge of ICT tools and related capacities remains important (Zhao et al., 2021). The UNESCO Global Framework for Digital Literacy (Law et al., 2018) highlights this as *Knowledge of Hardware and Software* (HW/SW).

Characteristics of knowledge building communities: The 12 KB principles

Knowledge Building (KB), as defined by Scardamalia and Bereiter (2010), refers to a community's intentional and collaborative efforts to create and improve knowledge. As a pedagogical approach, KB prioritizes collective knowledge advancement through meaningful social interactions and shared work, shifting the focus from individual learning to group knowledge creation. Learners are encouraged to contribute ideas, critically evaluate perspectives and refine understanding through deep discussion and shared explanations or models. Public knowledge creation and group assessment are emphasized (ibid).

Scardamalia (2002) identified 12 KB principles that characterize the metacognitive discourse of KB communities (see Table 1). These principles are often used to code and assess the quality of students' metacognitive engagement (eg, van Aalst & Chan, 2007). An analysis of collaborative discourse among 250 students in Hong Kong's 'Peer Tutoring Project' showed that the emergence of these principles follows three phases: open idea exploration, progressive inquiry and socio-metacognitive orientation (Law, 2005). Notably, two principles reflecting a communal habit of mind were not observed in that study. Subsequent research (eg, Feng et al., 2021) also found a developmental trajectory: starting with idea sharing, moving to collective cognitive responsibility and advancing to progressive KB.

The role of digital competence in scaffolding interdisciplinary knowledge building

Understanding the relationship between digital competencies and knowledge building (KB) processes is essential for theorizing how GAI mediates KB. Communication and collaboration—key areas of digital competence—are central to effective collaborative problem-solving

TABLE 1 The 12 KB principles according to Scardamalia (2002) and their categorization into four KB orientations according to Law (2005).

KB orientations	Associated KB principles
1. Open exploration and sharing of ideas	• Community knowledge, collective responsibility (team building and collective benefit) • Democratizing knowledge (giving voice to all community members) • Idea diversity (valuing multiple perspectives)
2. Progressive inquiry orientation	• Epistemic agency (active learning and ownership) • Knowledge building discourse (establish a culture of accepting individual differences; encourage evenness of contributions) • Improvable ideas (link, expand and improve ideas) • Constructive use of authoritative sources (authenticity of information)
3. Socio-metacognitive orientation	• Real ideas, authentic problems (give priority to understanding and addressing real life problems) • Rise above (transcending idea diversity towards deeper, higher-level understanding) • Embedded and transformative assessment (continuous monitoring and reflection on team progress)
4. A communal 'habit of mind'	• Symmetric knowledge advancement (everyone can learn and co-construct knowledge with others) • Pervasive knowledge building (transfer KB way of thinking and working to other subjects/contexts)

(Fiore et al., 2018; Van Laar et al., 2017). Research shows that these skills help create a constructive learning environment, support active idea sharing, regulate problem-solving and enable collective knowledge co-construction (Notari et al., 2014; Saab et al., 2005). For collaboration to be effective, students must know how to use digital tools to enhance team performance (Lane et al., 2023; Zhang & Hyland, 2023).

Interdisciplinary collaboration, which enriches idea diversity (a core KB principle), integrates perspectives from multiple fields to tackle complex problems. However, it also introduces challenges—such as differences in terminology, theories and knowledge bases—that can impede shared understanding and communication (Frigotto & Rossi, 2012; Klein, 2014). Overcoming these barriers requires strong commitment and open communication (Riggio & Saggi, 2015; Schmitz & Winskel, 2008). To succeed in authentic problem-solving with GAI tools, team members must leverage appropriate digital competencies at each stage of the collaborative knowledge building process.

Human–AI teaming in knowledge building contexts: A design challenge?

Cukurova (2024) contends that viewing AI merely as tools is too limited, advocating instead for human–AI teaming to extend cognition through hybrid intelligence systems—an area still underdeveloped. Prior research shows that effective technology-enhanced learning depends not only on tool design but also on the design of the broader learning context, including the physical and social environment, tasks, assessment and feedback (eg, Law, 2017). Unlike typical hackathons that attract technically inclined students, GAI hackathons engage interdisciplinary teams, offering a unique opportunity to explore how diverse learners interact with GAI and other digital tools to solve personally meaningful problems (Sajja et al., 2024). Findings from this study may thus shed light on pedagogical design features that support productive human–AI teaming.

RESEARCH QUESTIONS

In this study, we examine how three key attributes of Hackathon teams—team dynamics, digital competence and knowledge building (KB) characteristics—contribute to success in authentic problem-solving using GAI tools. Team dynamics refers to the evolving interactions, roles and performance within a team as members adapt over time (Burke et al., 2006; Kozlowski, 2015), with particular attention to the impact of membership changes on team performance. We selected a GAI Hackathon for its organizational openness and flexibility. This research addresses the following questions:

RQ1. Do team composition, structure and their changes over time influence Hackathon success?
RQ2. What digital competences do successful Hackathon teams demonstrate, and how are GAI tools used in these instances?
RQ3. What KB characteristics do different teams exhibit during the hackathon process, and what roles do digital competence and GAI tools play in the KB process?

RESEARCH DESIGN AND METHODS

The hackathon examined in this study was a campus-wide, co-curricular event that invited students to use GAI tools to address real-world challenges in five thematic areas: Education and Lifelong Learning, Social Inequality and Justice, Sustainable Development and Climate Action, Diversity, Equity and Inclusion, and Public Health and Well-being.

Study context, data collection and analysis

The four-week hackathon began in late September 2023. Launch day featured icebreaker activities to help students connect, form teams and register. Participants were introduced to the schedule and rules, followed by workshops on SDGs, game/prototype design and using Notion for collaboration. To encourage collaboration across academic levels, each team was required to include at least one undergraduate student and could have up to 10 members. Over the next four weeks, optional talks and workshops on AI tools, chatbot development, pitching and project completion were offered. Common workspaces were available for solution development and pitching practice. Each team had at least two mentors from academia or industry, and teams needing AI resources received free tokens and API services.

Students registering on launch day completed a pre-survey on their background information (faculty, program, year of study). Teams were required to submit an interim report on Notion at the two-week mark, detailing their project overview, progress, challenges and resource needs. On the final presentation day, teams pitched their solutions to a panel of academic and industry judges. Prototype code was submitted on GitHub the day before. Each presentation was followed by a 10-minute Q&A session. Prizes were awarded based on novelty/innovation, potential impact, feasibility/sustainability and ethical considerations. Teams competed in three parallel strands based on their topic, with each strand awarding a championship and a runner-up prize.

Participation in the Tips Award was optional. Teams entering the Tips Award were required to submit all materials within one week after the hackathon concluded. A judging panel decided on one championship, one runner-up and three merit Tips Awards based on the quality of reporting and reflection on the use of digital technology for collaborative teamwork and prototype development, project management, planning and organization, evidence of strategies used, ethical considerations and plans for future project development. After the hackathon results were announced, students were invited to participate in focus group interviews to further explore their learning experiences, particularly regarding interdisciplinary teamwork. However, due to students' busy schedules, the response rate was low.

Institutional ethics approval was obtained for collecting data via surveys, interviews, photos, videos and digital records during the hackathon. Only students aged 18 and above were eligible to participate, which excluded some first-year undergraduates. A total of 20 teams registered on launch day; 3 teams dropped out, and 17 teams pitched on the final day. Nine teams participated in the Tips Award, but only seven provided sufficient documentation to address research questions 2 and 3. Notably, all seven of these teams won at least one award. Table 2 summarizes the projects of these seven teams, the digital tools they used, and the awards they received, beginning with the teams that won the more prestigious or more awards.

Data on team composition, structure and changes over time for the seven teams were compiled from participants' registration information, interim reports, team member details on Notion and final presentations to address RQ1. For RQ2 and RQ3, data were collected from students' activity log entries on Notion, interim reports, transcripts of final presentations and Tips Award submissions. These materials were segmented into ‘meaning units’—one to three sentences containing sufficient context to interpret the students' descriptions or references. In total, 793 data segments were identified, with 121 segments from activity logs

TABLE 2 Summary of the awards won by the 7 teams and their respective hackathon problem.

Team # & awards won	Project overview	Tools used to construct the prototypes
TM3 1st & Tips 2nd	Provide improved image-to-text generation models to convert old books with low quality prints into machine readable texts easily understandable by visually impaired students	REACT components, the IDE of VScode
TM14 1st & Tips 3rd	Using voice-cloning and audio-to-avatar technology to support hearing-impaired students	CSS; Django; HTML; Javascript; Colab; Python
TM7 1st	An AI-powered language learning app focused on teaching Cantonese to English-speaking ethnic minorities in Hong Kong	Landbot (a low code platform)
TM17 2nd & Tips 3rd	An GAI powered App to provide customized financial and employment services to Foreign Domestic Helpers	Vue.js for the front-end, the MERN (MongoDB, Express.js, React, Node.js) stack
TM19 2nd & Tips 3rd	An online platform that helps professional psychiatrists monitor diagnosed ADHD patients by transforming sensor signals from patients into brief daily reports and flag potential issues	REACT for UI in front-end, Teailwind CSS for prototyping UI, FastAPI for web backend
TM12 2nd	Use AI to provide personalized tutoring to students from disadvantaged backgrounds	ChatGPT
TM13 Tips 1st	A study planner that can generate customized study plans for workers with reskilling or upskilling needs and provide pointers to relevant learning resources	React.js library Python pytesseract

containing explicit timestamps provided by students. Content analysis of these segments was conducted to address RQs 2 and 3.

It should be noted that while we present both quantitative and qualitative findings, the quantitative results serve to provide a descriptive context rather than an inferential analysis.

RESULTS

Team composition, structure and hackathon success

A total of 162 students registered in one of 20 teams at the hackathon launch, with 125 students persisting to the final presentation. Of the 37 students who dropped out, 25 were from the three teams that withdrew entirely. Table 3 summarizes the distribution of participants across faculties. It shows that no students from the Medical faculty participated. One Dental faculty student registered but later dropped out. Engineering students comprised the largest disciplinary group, and their dropout rate (22%) was similar to the overall cohort (23%). The Social Science faculty had the highest dropout rate (40%), while Education had the lowest (7%). Students from the three teams that dropped out accounted for 68% of all dropouts. Figure 1 illustrates the team composition of both winning and dropout teams.

Comparing dropout rates, winning teams had a 14% dropout rate, while non-winning teams had a 5% rate; suggesting that dropout percentage did not negatively impact a team's likelihood of winning an award. The remainder of this paper presents a detailed analysis of data from the seven teams with adequate data (all of which won at least one award) to address the three research questions.

Team composition, organization and interdisciplinary collaboration

This section examines how team composition, structure and their evolution over time influenced hackathon success. As required by the rules, all teams included members from at least two faculties. The largest disciplinary group was Engineering undergraduates, followed by Education postgraduates. Each of the seven teams had at least one Engineering student. Notably, TM13, which had the highest concentration of technical expertise with seven engineers among their eight members, also demonstrated outstanding organization, workflow management and systematic work practices by winning the first prize in the Tips Award. However, this team did not receive any hackathon awards.

Team membership diversity brings valuable ideas and expertise diversity

To gain deeper insight into students' experiences working in interdisciplinary teams, we reviewed transcripts from post-hackathon interviews along with other relevant data for qualitative analysis. The leader of Team 3—an engineering undergraduate whose team included five engineering and four non-engineering students and was among the top winners—provided a vivid account of the diverse contributions made by team members from different disciplines. In the post-hackathon interview, he reflected on what he described as the ‘narrow-minded thinking’ of the team's five engineers, including himself:

> And … engineers [tend to] have a very narrow way of thinking. I don't want to say this formally. But yeah, but feel like we do have a kind of short-sighted[ness] problem.……

TABLE 3 Summary of the number of student participants at the start and end of the Hackathon for each of the ten faculties in the university.

	Architecture	Arts	Business & economics	Dentistry	Education	Engineering	Law	Medicine	Science	Social science	Unknown	Total
All teams												
Start	3	24	16	1	15	67	6	0	11	10	7	160
End	2	20	14	0	14	52	5	0	7	6	3	123
Dropouts	1	4	2	1	1	15	1	0	4	4	4	37
Dropout rate	33%	17%	13%	100%	7%	22%	17%	NA	36%	40%	57%	23%
Winning teams												
Start	1	5	4	0	10	32	2	0	3	2	0	59
End	1	5	4	0	9	27	2	0	2	1	0	51
Dropouts	0	0	0	0	1	5	0	0	1	1	0	8
Dropout rate	0%	0%	0%	NA	10%	16%	0%	NA	33%	50%	NA	14%
Non-winning teams												
Start	1	15	12	0	5	26	3	0	5	6	3	76
End	1	15	10	0	5	25	3	0	5	5	3	72
Dropouts	0	0	2	0	0	1	0	0	0	1	0	4
Dropout rate	0%	0%	17%	NA	0%	4%	0%	NA	0%	17%	0%	5%
Quitting teams[a]												
	1	4	0	1	0	9	1	0	3	2	4	25
	33%	17%	0%	100%	0%	13%	17%	0%	27%	20%	57%	16%

[a]Three out of the original 20 teams that enrolled dropped out from the Hackathon entirely. The figures indicate the distribution of the 25 students in these quitting teams across faculties.

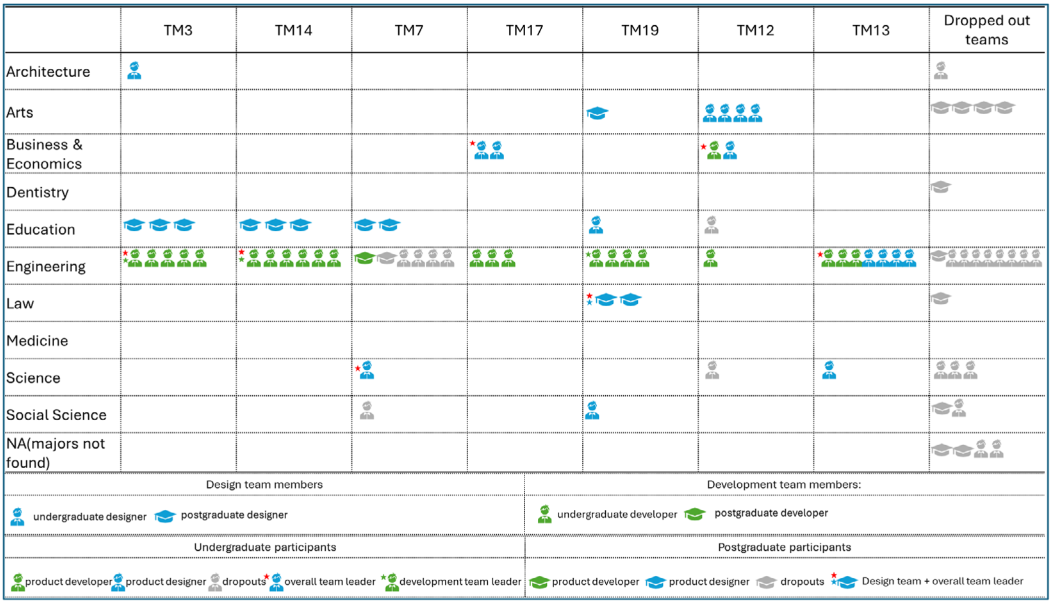

FIGURE 1 Distribution of participants across the different faculties in the 7 winning teams and the 3 dropped out teams, respectively.

> And when I saw the engineering team's ideas, [they] were all very similar…. because we're engineers, we see possibilities, right? And we try to think of possible problems. I mean problems that are possible to solve. And that is very narrow-minded thinking, at least in my experience.

He also emphasized how interdisciplinarity in team membership brought valuable diversity of ideas, which played a crucial role in shaping the project's direction:

> But if you have a lot of different people seeing a problem in a different perspective, if, like that becomes, the experience becomes really enriching. ….
>
> And there was one member from faculty of education, who suggested that this, this product, this is a problem, and we should solve it. And everyone was, Yeah, oh, wow! And that was the first kind of "Aha moment" that, oh, this team is going to work well! Because we had [an] engineering team, [that] was also very technically gifted.

Another observation highlighting the influence of disciplinary backgrounds on roles of members was in the teams' structures. To improve efficiency, streamline teamwork and to address scheduling challenges, all seven teams organized themselves into two sub-teams: a *product design team* to focus on research and specification of the prototype features, and a *product development team* to handle prototype construction. Each team also appointed an overall leader to coordinate between the two sub-teams. Notably, all engineering students with the exception of those in Team 13, participated in the product development sub-teams within their respective projects.

In their Tips Report, Team 13 mentioned as a major challenge that they only discovered after consulting their mentor near the end of the hackathon that a similar product already existed. Their limited idea diversity, stemming from a lack of non-engineering perspectives, might have constrained their success despite their technical expertise and diligence.

Managing idea diversity, member dropout and team performance

Maintaining a cohesive team proved challenging, as shown by the dropout rates in Figure 1. Two winning teams experienced member losses. TM12, the runner-up, started with nine members from five faculties but lost two—one from Education and one from Science—ending with seven members from three faculties. TM7 suffered six dropouts, including five engineering students from the original six, reducing the team from ten to four just a week before the Hackathon finals. The remaining four members from three faculties demonstrated strong commitment and effective interdisciplinary collaboration, earning a Hackathon championship. TM7's 'Tips Report' excerpt below describes the remaining members' perception:

> 6 of our members dropped out amid the hackathon as **they couldn't see the idea going forward, only 4 remained for the final presentation/demo**. The 4 of us had to endure the loads of burden and persist through ideation, prototyping and pitching.
>
> We tried to not let that affect us emotionally. Our goal had always been on prototyping and pitching the idea. If we had a second chance, more emphasis would be placed on motivations of individual members.

Managing idea diversity among members from different disciplines is a significant challenge. For TM12 and TM7; however, member dropouts ultimately facilitated goal alignment and a shared vision, contributing positively to their Hackathon performance.

Digital competence and role of GAI tools in hackathon performance

As shown in Figure 1, the number of engineering students varied widely across the seven teams, ranging from one to seven. To address RQ2—*What digital competences do successful Hackathon teams demonstrate, and how are GAI tools used in these instances?*—we analysed all 793 data segments and identified 347 that reflected students' digital competences. These were coded using the five competence areas according to the DigComp 2.2 framework and a sixth competence—knowledge of hardware/software (HW/SW)—based on the UNESCO Global Framework for Digital Literacy (Law et al., 2018).

Table 4 summarizes the number of digital competence-related segments per team across the six digital competence areas (DCAs), within which the numbers that involved GAI use. For example, of the 27 instances coded as information and data literacy (IDL), 16 involved GAI. Since some segments reflected multiple competences, the 347 segments yielded 467 DCA codes, 206 of which (44%) involved GAI use. Two coders independently coded all segments, achieving high intercoder reliability (Cohen's $\kappa = 0.905$).

The most frequently observed competences were digital content creation (DCC) and problem-solving (PS), followed by HW/SW, communication and collaboration (C&C), safety and IDL. GAI usage varied across areas: IDL had the highest proportional use (59%), followed by PS (55%), HW/SW (44%), DCC (39%), safety (33%) and C&C (7%).

It is important to note that the coded instances of students' digital competence likely represent only a portion of the skills they employed during the hackathon, as we lack comprehensive records of all interactions and performance. The frequency of observed competences also may not reflect their actual importance. For instance, Information and Data Literacy (IDL) appeared least often but may be most familiar to students, and thus less likely to be explicitly mentioned. This study focuses more on the relative role of AI use in the

TABLE 4 Summary of the distribution of digital competences as well as those that include the use of AI demonstrated in the data segments collected from the 7 winning teams.

	TM3	TM14	TM7	TM17	TM19	TM12	TM13	Row Total	Row total (AI %)
IDL	2	10	2	1	3	3	6	27	
IDL (AI)	1	8	2	0	1	1	3	16	59%
C&C	17	3	2	9	3	11	12	57	
C&C (AI)	0	1	0	1	1	0	1	4	7%
DCC	13	20	13	28	15	18	24	131	
DCC (AI)	1	16	6	11	0	11	6	51	39%
Safety	4	5	4	12	4	7	9	45	
Safety (AI)	2	2	1	3	1	2	4	15	33%
PB	13	33	12	17	8	20	18	121	
PB (AI)	3	17	8	8	4	19	8	67	55%
HW/SW	11	22	15	13	6	9	10	86	
HW/SW (AI)	4	10	10	6	1	3	4	38	44%
DC total	60	93	48	80	39	68	79	467	
DC total (AI)	11	54	27	29	8	36	26	191	41%
TM total AI%	18%	58%	57%	35%	20%	53%	33%		

different competence areas. The next section presents the role of GAI tools, ordered by the relative frequency of GAI use in each area.

For **information and data literacy** (IDL), ChatGPT was the most commonly used GAI tool. It served primarily as an alternative to search engines and as a source of information to refine solution prototypes.

In the domain of **Problem-solving** (PS), digital competence was evident throughout the solution development process, with GAI playing varied roles depending on the teams' technical expertise and solution types:

- *Skill augmentation for less technical teams*: TM12 and TM14 used ChatGPT to grasp technical concepts, develop and debug prototypes. TM12 also relied on ChatGPT to interpret the codes generated by GAI tools due to limited programming knowledge.
- *Technology integration for technically proficient teams*: TM13 and TM17 combined GAI with programming languages (Python, JavaScript) and collaborative IDEs (GitHub, Google Colab). TM19 employed advanced tools like HKU AI CV Clinic and OpenCV PyTess for ADHD care solutions.
- *Media processing for media-intensive solutions*: TM3 enhanced OCR for visually impaired students using image-to-text models. TM14 developed sign language teaching tools for hearing-impaired learners using Stable Diffusion and ControlNet.

Hardware/Software Knowledge (HW/SW) was critical for certain solutions. TM3, for example, had to identify specialized AI tools capable of transcribing dated manuscript prints and reconstructing missing text based on context.

GAI tool use for **Digital Content Creation (DCC)** was diverse, depending on the topic and team expertise. TM14 leveraged Tome AI and Canva for pitch decks and ChatGPT and Poe.com for website content creation. In contrast, TM19 did not use GAI tools for DCC; TM3 used them only once across 13 coded instances. All teams, however, used conventional tools like Google Slides, PowerPoint and Vue.js for presentations and front-end development.

Safety encompassed ethical concerns such as data privacy, bias and inclusivity. All seven teams acknowledged the importance of addressing these issues during prototype development. TM19 faced challenges in collecting sensitive data due to privacy concerns and opted to use a publicly available dataset for training their prototype. Some teams also used GAI tools to identify and address data privacy issues during the design and development process. TM13 discussed how they handled ethical issues in their Tips Report:

> We paid close attention to ensure that the algorithms were fair, transparent, and unbiased, and that they did not perpetuate existing inequalities or reinforce discriminatory practices. … ensure that AI algorithms are developed and trained using diverse and representative datasets, regularly audited for bias, and thoroughly tested for fairness. Transparency in how algorithms make decisions and providing explanations when necessary, can promote trust and mitigate potential ethical issues.

Communication and Collaboration (C&C) was primarily supported by digital tools like WhatsApp, Zoom and Microsoft Teams. AI appeared in only 4 of 57 coded C&C instances, which were not conventional team communications. In three cases, AI acted as a collaborator—offering brainstorming input, suggestions and technical advice. In the fourth, TM19 described their solution as enabling patients to become ‘a collaborator within the process of treatment [with the psychiatrist]’, by facilitating more data-based communications with the psychiatrist by providing summaries of patients' daily reports and ‘flags’ for potential issues through the App.

Knowledge building, digital competence and GAI use

To address RQ3, we first identify Knowledge Building (KB) characteristics demonstrated by the hackathon teams. Each of the 793 data segments was coded for evidence of any of the 12 KB principles. Initially, two coders were to code all segments independently, but due to unforeseen circumstances, the second coder only completed 725 segments. Given the large number of coding categories ($n=12$), Cohen's Kappa may underestimate agreement. Therefore, percentage agreement was used, ranging from 97.2% to 100%. Table 5 summarizes the coding results.

Table 5 shows that the most prevalent Knowledge Building (KB) characteristic (for explanations, see Table 1) was *socio-metacognitive orientation*, followed by *progressive inquiry* and *open exploration and sharing*. The least frequent was *communal habit of mind*, appearing in only 5% of KB-related segments. No clear correlation was found between the distribution of KB characteristics and team performance or awards.

Of the 518 segments coded as reflecting Knowledge Building (KB) characteristics, only 100 included timestamped entries from the Notion activity log. This means 21 of the 121 activity log entries did not contain KB-relevant data. Table 6 presents the distribution of KB orientation codes across the seven teams over the four-week period. The following section explores the week-by-week emergence of KB orientations, using examples from the full set of 518 segments to more fully illustrate the nature of KB activities under each orientation.

Week 1: From open exploration to progressive inquiry

Table 6 reveals a clear shift in KB engagement over time, with Week 1 dominated by *open exploration and sharing*. This likely reflects the teams' early efforts to build a collaborative culture and define their hackathon challenge. Within this orientation, the most frequent KB principle was *community knowledge and collective responsibility* (41%), evident in meetings

TABLE 5 Distribution of identified instances of KB principles in the data gathered from the interim reports, presentation transcripts and Tips award submissions of the 7 teams.

		By team						
		TM 3	**TM 14**	**TM 7**	**TM 17**	**TM 19**	**TM 12**	**TM 13**
Open exploration & sharing (OS) (total = 94)		**26**	**15**	**14**	**9**	**7**	**7**	**16**
OS1	Community knowledge	10	8	5	3	4	5	5
OS2	Democratizing knowledge	5	4	4	3	3	2	7
OS3	Idea diversity	11	3	5	3	0	0	4
Progressive inquiry orientation (PIO) (total = 148)		**27**	**26**	**14**	**18**	**19**	**27**	**17**
PIO1	Epistemic agency	6	5	4	3	1	5	5
PIO2	Knowledge building discourse	9	15	9	8	11	19	6
PIO3	Improvable ideas	9	2	1	3	0	3	2
PIO4	Constructive use of authoritative sources	3	4	0	4	7	0	4
Socio-metacognitive orientation (SMO) (total = 250)		**41**	**43**	**24**	**51**	**34**	**23**	**34**
SMO1	Real ideas	17	21	12	21	22	14	17
SMO2	Rise above notes	9	12	4	20	7	8	16
SMO3	Embedded and transformative assessment	15	10	8	10	5	1	1
Communal 'habit of mind' (CHM) (total = 26)		**3**	**4**	**9**	**2**	**3**	**4**	**1**
CHM1	Pervasive knowledge building	0	0	0	0	1	0	1
CHM2	Symmetric knowledge advancement	3	4	9	2	2	4	0
	Team total	**97**	**88**	**61**	**80**	**63**	**61**	**68**

TABLE 6 The distribution of the 4 KB orientations demonstrated by all 7 teams over the 4 weeks.

	Week 1	**Week 2**	**Week 3**	**Week 4**	**Orientation total**
Open exploration & sharing (OS)	13	0	0	0	13
Progressive inquiry orientation (PIO)	20	11	5	4	40
Socio-metacognitive orientation (SMO)	1	11	13	15	40
Communal 'habit of mind' (CHM)	0	0	0	7	7
Week total	34	22	18	26	100

to clarify rules, assign tasks and propose research directions. *Democratizing knowledge* (30%) and *idea diversity* (29%) were also prominent.

Reaching consensus on a shared goal proved challenging. TM13 and TM14 held multiple open discussions to incorporate diverse perspectives. TM3 used idea justification and voting to finalize their direction. TM7; however, made a quick decision with minimal debate; resulting in internal conflicts that led to six members leaving just a week before the final presentation.

Progressive inquiry also emerged in Week 1, particularly after teams selected their challenge focus. Teams engaged in knowledge building discourse to define prototype features, including user interviews and consulting authoritative sources. They identified knowledge gaps—such as limited understanding of GAI—and demonstrated *epistemic agency* by attending workshops, seeking peer and mentor support and using ChatGPT to deepen their understanding.

Week 2: Progressive inquiry and socio-metacognitive engagement

Progressive inquiry continued into Week 2, accompanied by the emergence of *socio-metacognitive* KB characteristics as teams began their prototype development. *Rise above* was evident in the design sub-teams' synthesis of research findings and identification of required prototype features, which guided the development sub-teams' prototype construction efforts.

The principle of *real ideas and authentic problems* manifested differently across sub-teams. Design teams grappled with understanding user needs and related design challenges, while development teams faced technical and engineering hurdles. TM17 and TM19, for example, struggled to obtain sufficient training data for their chatbots due to privacy concerns. TM17 ultimately used a publicly available dataset from the literature, while TM19 formed a legal and ethical subgroup to address data sensitivity and compliance issues.

Week 3: A strong socio-metacognitive focus

In Week 3, all teams concentrated on prototype development, with a notable emphasis on *socio-metacognitive* KB principles. In addition to the principles of *real ideas* and *rise above*, the teams demonstrated *embedded and transformative assessment* to advance their prototype development, testing and refinement. Teams became increasingly aware of potential biases and inaccuracies, especially those introduced by GAI tools. These concerns varied by project; prompting teams to adopt different mitigation strategies.

Week 4: Socio-metacognitive reflection and emerging communal habit of mind

In the final week, most data segments reflected a *socio-metacognitive* orientation, with a *communal habit of mind* also emerging, primarily through *symmetric knowledge advancement* as students reflected on their hackathon experiences. Teams differ in the content of their reflections. TM7 focused on communication and collaboration challenges in multidisciplinary teams as they grappled with the impact of losing 6 out of 10 members. Other teams reflected on the role of digital tools in facilitating collaboration or the use of GAI in enhancing learning. TM14 and TM12, which used GAI extensively, became more aware of its limitations. TM13, which relied on Python for prototyping, expressed an interest in exploring GAI for future problem-solving.

Human–AI collaboration in the knowledge building process

Over the four weeks, teams exhibited evolving patterns of digital tool use and digital competence. For example, during the *open exploration and sharing* phase, *communication and* *collaboration (C&C)* competence was most prominent, supported by tools like WhatsApp for daily messaging, Zoom for meetings and Notion for documentation. TM13 also established a shared Google Drive repository early on. Aligned with the *progressive inquiry* orientation, students demonstrated competences in *digital content creation (DCC)* and *hardware/software knowledge (HW/SW)*.

Compared to conventional digital tools, GAI tools played more versatile and diverse roles, including serving as brainstorming partners, junior engineers explaining code and technical consultants offering tailored suggestions. Reviewing the teams' descriptions of their interactions with Generative AI (GAI) systems throughout the hackathon reveals a dynamic and evolving relationship between students and the AI tools they used. TM14 captured this process vividly in their interim report:

> Since we started working on the project, our understanding of the problem and solution has evolved significantly. …… Through our work with Generative AI, we have realized the potential of this technology to bridge gaps in education and provide customized learning experiences. Our understanding of the capabilities and limitations of Generative AI has also grown, enabling us to refine our approach and optimize the use of these tools for our project.

In the remainder of this section, we describe the roles played by GAI for teams with varying characteristics across different stages of the hackathon process. During ***ideation***, GAI tools acted as brainstorming partners, offering suggestions and helping clarify ideas. For example, TM17 noted in their activity log, '*When I have a brief idea and I need some detailed points to enrich my point, I can prompt my idea to ChatGPT, which enables me to create a more detailed idea'*.

To gain ***mastery of technical skills*** necessary for prototype development, teams that lacked sufficient programming knowledge, such as TM12 and TM14, used GAI tools to understand technical concepts, debug prototypes and seek advice on technical challenges. The technically weakest team, TM12, relied on ChatGPT to interpret the codes generated by GAI tools.

In the ***prototype development*** stage, all teams employed AI tools, with the specific tools varying according to project needs. TM19, for instance, used GPT-3.5-turbo for data summarization and the Whisper model for audio transcription in developing their ADHD support App. TM14 used Stable Diffusion, a text-to-image generation model, to create sign language models.

Finally, for ***presentation preparation and website development***, teams used tools like Tome AI for pitch decks and React for building user interfaces.

Several teams explicitly described their interactions with GAI as a collaborative process involving negotiation of understanding. TM12, in particular, provided detailed examples in their activity log that illustrate how they navigated this process. These excerpts highlight moments where the team engaged in *iterative dialogue* with GAI tools—posing questions, interpreting responses and refining their back-and-forth exchanges to seek mutual understanding to achieve their goals:

> ChatGPT may understand my questions in an incorrect way. I need to prompt a more detailed message to ChatGPT (such as more detailed description on the outcome that I want to achieve) in order to avoid misunderstanding. … I need to ask for clarifications from ChatGPT if I have anything that I am unsure about.
>
> … Debugging complex code issues can be difficult with ChatGPT as the length of messages we [can] prompt is limited. … Hence, we need to copy the relevant

> codes only [to ChatGPT] and understand the codes created in order to incorporate them into our prototype.

It is clear from the students' descriptions that the roles played by AI during the hackathon process were various and reflected all three of Cukurova's (2024) AI use conceptualizations. For instance, using AI tools to create prototypes and pitch decks reflects automation; learning programming and debugging through AI suggests internalization; and brainstorming with GAI exemplifies collaboration to extend human intelligence. Notably, students demonstrated the ability to fluidly shift between these modes during problem-solving and knowledge building. While they offloaded some cognitive tasks to AI, these actions were intentional and critically evaluated, with no evidence of metacognitive laziness—a known risk in AI-assisted learning (Fan et al., 2025).

DISCUSSION

GAI augment collaborative problem-solving

This study offers an initial exploration into how GAI tools can enhance collaborative problem-solving around real-world challenges in contemporary society. Our findings highlight the potential of GAI to augment students' digital competence, boost productivity and foster creativity in digital solution development, regardless of their prior technical expertise. Novice developers used tools like ChatGPT as coaches to support prototype development, suggest code blocks and debug solutions. More technically proficient students leveraged GAI to build advanced systems. Interestingly, students with less experience in application development appeared to benefit more from GAI, using it to bridge gaps in digital competence. Notably, technical expertise did not determine a team's success in the GAI hackathon.

It is important to note that hackathon awards were based on prototype quality alone. While winning teams clearly articulated the challenges they aimed to address and presented prototypes that demonstrate strong proofs of concept, delivering a viable, robust and market-ready product would still require more advanced digital competence. Nonetheless, our findings suggest that appropriate use of GAI tools can lower the technical threshold for creative problem-solving.

Human-human and human–AI collaboration in GAI hackathon

Interdisciplinary expertise also emerged as a key factor in hackathon success. Among the six teams that won hackathon awards, three had a majority of members from non-engineering backgrounds, and the remaining three had at least 33% non-engineering representation. In contrast, TM13—recognized only for high process quality through winning the first prize in the Tips Award—had just one non-engineering student among eight members. While the scale of this study limits broad generalization, the findings underscore the value of cultivating fluency in interdisciplinary collaboration, especially as GAI tools reduce barriers for participants without technical backgrounds.

Our findings also shed light on the conditions for fostering successful interdisciplinary collaboration. An open exploration and sharing environment in the early stages of the hackathon was critical for sustainable teamwork. Teams such as TM3, TM13 and TM14 engaged in open discussions and debates around diverse ideas, which helped clarify goals and strengthen commitment to collaborative knowledge building. In contrast, TM7's lack of early open sharing and debate contributed to internal conflict and the dropout of six members. While homogenous teams like TM13 may experience fewer conflicts, they may also lack the idea and expertise diversity needed to stimulate creative thinking and robust debate.

A particularly compelling observation from this study is that some students viewed GAI as a collaborator in their problem-solving process—engaging in brainstorming, offering suggestions and providing technical advice. One team even conceptualized their technology platform as a mediating collaborator between psychiatrists and patients. This aligns with growing research interest in GAI as a collaborator (Sharples, 2023) and in human–AI teaming (Cress & Kimmerle, 2023; Xu & Gao, 2023; Zhang et al., 2021) and can be considered as an example of GAI use that extends human cognition through coupled human–AI hybrid intelligence systems.

Pedagogical implications

Earlier in this paper, we argued that AI literacy should be contextualized within a broader framework of digital literacy. Our analysis confirms that all seven teams demonstrated a wide range of digital competences, extending beyond AI/GAI use. Even when the focus is on developing core components of AI literacy in the literature: technical knowledge, skills and ethical awareness (eg, Long & Magerko, 2020), our findings have important implications for curriculum and pedagogical design. The context in which such literacy is acquired matters. The sophisticated and varied ways in which participants leveraged GAI, along with their attention to ethical concerns, suggest that collaborative problem-solving contexts may be the most effective pedagogical model for developing AI literacy. Further, our findings show that for students committed to their goals, the Hackathon offered a meaningful context to fluidly engage with the modes of human–AI interaction outlined by Cukurova (2024), suggesting that GAI hackathons can be an effective pedagogical design for fostering hybrid intelligence.

LIMITATIONS

We acknowledge some limitations in this study. First, participants voluntarily joined the hackathon and the Tips Award, making the data collection less controlled. Second, our analysis could only focus on successful cases due to attrition and data availability. Third, although we managed to draw a comprehensive picture of teams' collaborative problem-solving through the Tips Award and the Notion logs, much of the collaboration happens beyond our scope of analysis. Our analyses only shed light on how students work collaboratively with each other and with GAI using their self-reported data. Fourth, generalizability is further constrained by the scope of the hackathon event being held in only one Hong Kong publicly funded university. Future research should explore the role of GAI in authentic collaborative problem-solving contexts beyond hackathons to better understand these dynamics.

CONCLUSION

The hackathon provided a unique opportunity for higher education students to collaborate on meaningful, self-chosen challenges. Our analysis focused on the seven successful teams and demonstrated GAI's potential to augment collaborative problem-solving in authentic educational contexts. We conclude that the success depended on collaborative teamwork, diverse perspectives and digital competencies rather than technical expertise alone. GAI served multiple roles (eg, as automation, augmentation and collaboration partners) in the process of knowledge building in interdisciplinary teams. The findings suggest that pedagogical approaches emphasizing collaborative inquiry and human–AI interactions in the context of addressing real-world challenges can effectively foster the *holistic development* of digital competencies, including AI literacy, as well as collaborative knowledge building in interdisciplinary teams.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

As it is not feasible to remove personal identifiers from the data, it would not be made available to third parties.

ETHICS APPROVAL STATEMENT

The ethics of this study has been approved by the Human Research Ethics Committee of the University of Hong Kong.

PATIENT CONSENT STATEMENT

Not applicable.

PERMISSION TO REPRODUCE MATERIAL FROM OTHER SOURCES

Not applicable.

CLINICAL TRIAL REGISTRATION

Not applicable.

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