Research Article

Building Proficiency in GAI: Key Competencies for Success

Einat Grimberg[1], **Claire Mason**[1]

1. Data61, Sydney, Australia

The rapid proliferation and adoption of generative Artificial Intelligence (GAI) underscores its ease of use. However, there has been limited research exploring what constitutes proficient use of GAI and what competencies underpin it. In this study, we adopt a grounded approach and semi-structured interviews to explore how twenty-five expert GAI users (all knowledge workers) define, exemplify, and explain GAI proficiency. A purposive sampling approach was adopted with the aim of capturing input from experts from a range of occupations and sectors towards answering three questions. First, can we identify the characteristics that differentiate proficient (more effective) use of GAI? Second, what competencies are seen to underlie proficient use of GAI? Third, what benefits are associated with more proficient use of GAI tools? Analysis of the descriptions shared by the experts revealed four aspects of GAI proficiency: effective prompting, informed and responsible choices, diversity of use, complexity of use, and frequency of use. In addition, the following themes emerged from the analysis of the competencies supporting more proficient use of GAI: GAI literacy, domain expertise, communication skills, metacognition skills, curiosity and inquisitiveness, flexibility and adaptability, diligence, and (in some contexts) information technology skills. More proficient use of GAI was seen to have benefits ranging from improved productivity, higher quality output, and more original work. By offering a comprehensive framework for effective use of GAI, grounded in real-world experience, this study guides further research and substantiates the continuing relevance of human skills, knowledge, and mindsets when working with GAI tools.

Corresponding authors: Einat Grimberg, einat.grimberg@data61.csiro.au; Claire M. Mason, Claire.mason@csiro.au

1. Introduction

Generative Artificial Intelligence (GAI) refers to a broad category of AI solutions that can identify patterns learnt from vast datasets and generate new content that is often indistinguishable from human-generated content[1]. The adoption rate of GAI tools such as OpenAI's ChatGPT or Dall-E has been unprecedented[2][3],

 doi.org/10.32388/INFMMJ

reaching 100 million users within two months after its launch[4]. According to some surveys, 75% of knowledge workers use GAI at work today[5]. This rapid adoption can be attributed, in part, to their ease of use and flexibility. Their conversational capability means that they can be used without prior training or coding experience, and their flexibility means that they have broad application and can be harnessed across multiple domains[6][3] and at different stages of task performance[7].

As well as being easy to use, GAI tools appear to offer important performance advantages. Randomised control studies reveal that, on average, these tools improve users' productivity and quality in knowledge work ranging from programming[8], legal work[9], customer service[10], and consulting work[11]. Nevertheless, in these same studies, the researchers noted instances where the tools actually lowered workers' performance on the task. Errors noted in these studies may well be magnified if GAI tools are used on tasks for which workers do not have prior training and work experience. This highlights the importance of proficiency in using GAI tools effectively. Proficiency involves not only understanding how to use the tools but also applying them in a way that maximizes their potential while minimizing errors. There is therefore an urgent need for research that explores the question of what constitutes proficient use of GAI tools and what competencies (skills, knowledge, or mindsets) workers need to use GAI tools proficiently.

Williams & Fletcher[12] define Job-Specific Task Proficiency as "the degree to which the individual can perform the core substantive or technical tasks that are central to the job. They are the job-specific performance behaviours that distinguish the substantive content of one job from another" (p.143). This definition highlights the behavioural, performative aspects of carrying out a task. In the context of GAI tools, proficient use can be seen as the ability to perform tasks effectively and efficiently using these tools, leveraging the right competencies to achieve high-quality outcomes.

Competencies, on the other hand, are the set of qualities that support the proficiency. Bartram et al. [13] introduce a model of competency that includes competencies, its context, and results. They distinguish between competencies that are sets of desirable behaviours instrumental in the delivery of desired results or outcomes, and "competency potential", which are the individual attributes necessary for someone to produce the desired behaviours. According to the authors, these attributes are not always reflected in actual behaviour, since the behaviour that an individual displays is moderated by the context. The result component of their model refers to the outcomes or goals of behaviour.

Hlavac[14] defines skills as "either a demonstration of procedural knowledge or the capability to demonstrate procedural knowledge". He emphasises the learning element in competencies. His "knowledge, skills, and abilities" triad refers to qualities that a person has acquired (usually through formal training, even if this is not the only means for these to be gained). He adds that these three elements are outcomes of formal training and experiential learning[15][16][11][17][18][8].

 doi.org/10.32388/INFMMJ

This study aims to understand the competencies - skills, knowledge, and mindsets - underlying proficient GAI use and how they contribute to the benefits derived from using GAI tools. To this end, we interviewed a diverse group of expert GAI users, capturing their descriptions of effective and ineffective use of GAI. Their examples were used to characterise proficient use of GAI tools, analyse the competencies perceived to be differentiating effective from ineffective use of GAI, and identify the benefits derived from such effective use.

1.1. Skills and knowledge for GAI tools

A considerable portion of both public discourse[19][20][21][22] and scientific literature[23][11][24][25][26][27] on skills needed for using GAI tools has primarily focused on prompting skills. Prompts are essentially requests made to GAI tools to perform specific tasks, serving as the primary form of interaction between the user and the GAI system. There is already some evidence as to the importance of prompts in achieving good output from GAI tools. Jiang et al. (2020) reported that precise prompt composition is critical in achieving the desired output, with semantically similar prompts yielding significantly different and sometimes even incorrect output. Effective prompting appears to be a challenge to non-AI-experts, and especially to people without programming skills[27]. However, research suggests that training on how to prompt can lead to greater productivity gains from GAI tools[11].

In the literature, attention has also focused on the potential risks of uninformed reliance on GAI tools, due to their widely reported ‘hallucinations’ (inaccurate, inappropriate, or misleading outputs) that these tools can produce. AI literacy is therefore often cited as a requirement for the responsible use of GAI[28][29][30][31]. Definitions of AI literacy abound, but they commonly refer to the ability to understand, use, and assess the ramifications of AI tools[30][32][33]. Experienced users of AI tools have been found to achieve higher scores on measures of AI literacy[34]. However, there is surprisingly little evidence to show that interventions designed to enhance AI literacy improve performance when working with AI tools.

Researchers suggest that effective use of GAI human skills, such as critical thinking[35], metacognition[36], intuition (Buchanan & O’Connell, 2006), and soft (communication) skills, are advantageous to complement the AI and enhance its output[37]. A recent study by Annapureddy et al.[38] proposed twelve key competencies for understanding and using GAI systems, including knowledge of the technology, prompting, programming, domain expertise, and knowledge of the ethical and legal implications of using GAI systems. However, their model was based on a literature review of mostly conceptual papers and other reviews, rather than empirical evidence. Another recent study of 692 business professionals working with GAI found that character-based traits and communication will be required to work effectively with GAI tools. The authors report that skills such as quantitative analysis, language skills, and written communication skills were commonly viewed as less

 doi.org/10.32388/INFMMJ

important for GAI-enabled workers[39]. In comparison, skills such as integrity, strategic vision, the ability to inspire others, and oral communication were becoming more important[39].

1.2. Contribution of this study

In this study, we adopt a grounded approach[40] to explore GAI expert users' views on competencies for working with GAI tools.

Our objective is to extend the existing discourse on the importance of prompting skills and AI literacy for the effective use of GAI tools by identifying the range of attributes (from skills, knowledge, attitudes, and mindsets) underpinning the effective use of GAI tools. This study informs three research questions:

1. How do users perceive effective and ineffective use of GAI?
2. What competencies are consistently linked to effective use of GAI?
3. What benefits are associated with effective use of GAI?

2. Methodology

2.1. Sample

We adopted a grounded approach to base our findings on real-world observations and allow new ideas to emerge[40]. A purposive sampling strategy captured insights from experienced and acclaimed GAI users across various roles and organisations, identifying cross-cutting GAI competencies (rather than sector- or occupation-specific). We reviewed online conference programs and newsletters to identify leading speakers and writers known for their GAI experience. Additionally, we drew upon our professional networks, asking colleagues to nominate peers considered 'expert users' of GAI. We deliberately sampled participants from diverse roles and sectors to identify highly generalisable user practices. The interviews were conducted between February and August 2024.

The purposive expert sampling approach yielded 25 interview participants, whose collective experience using GAI spanned 14 organisations and 17 organisational roles (Table 1 & Table 2). About one third of the participants were identified on social media, while the rest were approached as part of the authors' professional network.

	Role	Sector
P104	Owner & CEO of a design studio for mobile gaming	Creative industries
P105	Architect and head of architecture firm	Creative industries
P106	Research scientist	Science and Technology
P107	Creative director	Creative industries
P108	Research scientist	Science and Technology
P109	Teacher	Education
P110	Research scientist	Science and Technology
P111	Research scientist	Science and Technology
P112	Data scientist	Science and Technology
P113	Software engineer	Science and Technology
P114	Organisational development advisor	Science and Technology
P115	Educator	Education
P116	Organisational development manager	Science and Technology
P118	Legal practitioner	Legal services
P119	Legal practitioner	Legal services
P120	Academic	Education & Research
P121	Medical practitioner & Technology lead	Healthcare
P122	Medical practitioner & Technology lead	Healthcare
P123	Academic	Education
P124	CTO and academic	Creative industries
P125	Journalist	Media
P126	Legal practitioner	Legal services
P129	UX, design and IT professional	Science and Technology
P130	Educator and technology leader	Education
P131	AI consultant	Professional services

Table 1. Participants' Professional Background

Role	Creative industries	Education	Education & Research	Healthcare	Legal services	Media	Professional services	Science and Technology	Grand Total
Research scientist								4	4
Legal practitioner					3				3
Teacher / Educator		3							3
Organisational development professional								2	2
Medical practitioner & Technology lead				2					2
Academic		1	1						2
AI consultant							1		1
Creative director	1								1
CTO and academic	1								1
Data scientist								1	1
Journalist						1			1
Software engineer								1	1
UX, design and IT professional								1	1

Role	Creative industries	Education	Education & Research	Healthcare	Legal services	Media	Professional services	Science and Technology	Grand Total
Mobile gaming designer	1								1
Architect	1								1
Grand Total	**4**	**4**	**1**	**2**	**3**	**1**	**1**	**9**	**25**

Most participants had begun using GAI tools when ChatGPT launched in November 2022, giving them at least a year of experience by the time of the interviews. Prior to the study, we couldn't objectively verify their GAI expertise and relied on rules of thumb, such as peers' opinions or considering keynote speakers on GAI as having considerable expertise. We included individuals without clear programming expertise, as interactions with GAI tools differ between chatbox interfaces and programming apps. We aimed to include these different interaction approaches in the study.

2.2. *Interview Protocol*

The interviews were semi-structured, with some questions asked across all interviews, while others varied in response to interviewees' specific experiences and knowledge of GAI tools. Follow-up questions were added to delve deeper into the topics that emerged. Initially, participants described their experiences with GAI, including the tools they used, their purposes, and the length of usage. They were then asked to provide examples of effective and ineffective GAI tool usage in their work. We did not predefine effective GAI tool use, with the aim of understanding participants' perspectives. Finally, interviewees identified the competencies (skills, knowledge, or mindsets) they drew upon for effective GAI tool usage. It was trialed with a small group before main data collection, and feedback helped refine the questions for clarity and flow.

The interviews were held via video calls, with most interviews lasting approximately 45-60 minutes (with a few taking longer). Interviews were conducted by the authors. Participants had received an information sheet before the interview, based on which they provided informed consent, specifically agreeing to the recording and transcription of the interviews. Ethical clearance for conducting and analysing the interview data was obtained from the CSIRO Human Research Ethics Committee, ensuring that all procedures adhered to the Australian National Statement on Ethical Conduct in Human Research and posed a low risk to participants.

2.3. Analysis

The data analysis was carried out iteratively and collaboratively by the two authors of this manuscript, using the NVivo qualitative data analysis software[41]. The first stage of coding involved both authors independently coding the same two interview transcripts. At this stage, a code was created for every 'idea' contained in the transcript relating to the use of GAI. After this process, the authors shared their coding and agreed on a structure for organising these codes into themes. As coding continued, we developed a codebook which provided a detailed description for each of the commonly used codes, to support consistency in coding practice. As coding continued, the authors continued to discuss emerging codes and useful ways of structuring them. Once each transcript had been coded by at least one author, the coding structure was revisited and a framework for organising the themes in the data was agreed upon. At this point, all the coded material was reviewed to ensure that each theme was clearly differentiated.

Our analysis includes both stated and observed data. Stated data are participants' explicit reports, while observations are pieces of information not directly mentioned by participants but rather noticed by the interviewer or researcher through careful and critical examination of the data. These observations can include verbal and non-verbal cues (e.g., emphases, facial expressions, pauses), contradictions in description, gaps (what is not discussed), and so forth. This approach allows us to highlight concepts that are overlooked or silenced by the interviewees.

The quotes presented here are provided as originally stated by the participants (excluding fillers like "you know", "ok", and alike). Thus, these quotes maintain the natural flow of speech and may not be grammatically accurate.

3. Findings

The themes and connections that emerged from the interviews provide a framework for understanding proficient use of GAI, the competencies underpinning it, and its benefits or outcomes (see Figure 1 for a schematic representation). The findings are described accordingly along these three main categories: first, we illustrate how participants' descriptions of effective and ineffective GAI use reveal four facets of GAI proficiency. Next, we discuss the eight main 'GAI competencies', reflecting participants' descriptions of the skills, knowledge, and mindsets that support effective use of GAI. The competencies align with the common definitions of skills, knowledge, and mindset[18], which motivated us to keep these categories. Finally, we illustrate how these competencies and aspects of proficiency lead to the benefits derived from using GAI tools. The competencies, then, are viewed as necessary conditions for proficiency and the benefits. The subsections start by describing the Proficiency construct, laying the groundwork for outlining the associated competencies. Contrarily, the figure begins with competencies to show the directional interaction between the constructs.

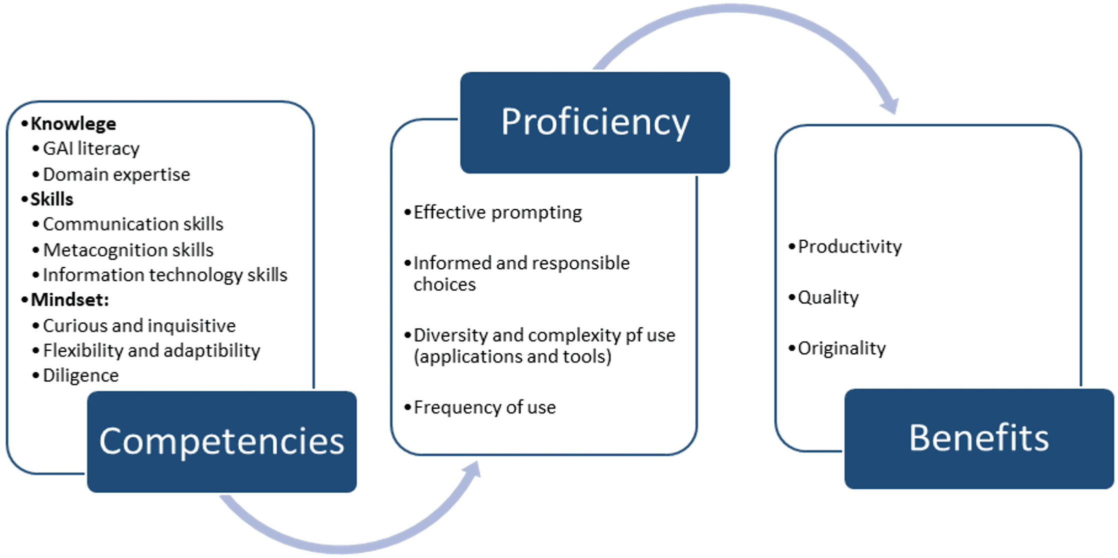

Figure 1. A framework of GAI users' competencies, proficiency, and benefits

3.1. GAI Use Proficiency

Adopting Williams & Fletcher's[12] definition, we concentrated on the behavioural aspects of using GAI as highlighted by participants to describe proficiency. Despite the diverse backgrounds of the study participants and the variety of tasks they used GAI for, four recurring themes emerged from the descriptions of effective and ineffective ways of working with GAI. Two themes, effective prompting and informed and responsible choices, were explicitly identified by participants as distinguishing effective and ineffective use of GAI. The other two themes, diversity of use and complexity and novelty of use, emerged during the analysis of participants' descriptions, rather than being explicitly identified or verified by participants.

3.1.1. Effective prompting

Prompting was usually the first thing that participants mentioned when asked about effective use of GAI. Effective prompting was described as the key to obtaining focused and relevant output from GAI tools. Effective use involves crafting queries that direct the GAI towards generating more accurate or appropriate responses than those often obtained with unrefined prompts. It starts with adopting a *conversational style* of a communication process between two parties and a gradual "back and forth" exchange over several steps, where each step builds on the previous one, narrowing or broadening the focus as needed, as interviewees explained:

> *[...] the ability to continue the conversation – [...] not many people get into it. [...] you can manage the conversation and* ***narrow it down and deepen it and continue the investigation*** *during the conversation [...] There are people who ask questions, get an answer. They find out whether or not they are moving forward. They take it and move on. There are those who ask a question and get an answer that they don't like. So, they ask it again and again and again until they get an answer that they do like and then they move forward with it. And there are those who really realise that you can have an intelligent conversation and investigate it in all kinds of directions and narrow it down and deepen it and draw out more angles. (P125)*

> *[...] all you have to do is start a conversation [...] It's like going to a pub and you know, you go up to a random person and say, "tell me what the population of Argentina is" [...] they might know. But if you start that conversation "Well, what can you tell me about Argentina?" [...] what's the produce? And [...] then the conversation [sic] knows it's about Argentina. What's the population growth?" (P106)*

Notably, providing context is a vital element of effective conversation. Secondly, good prompting involves *providing context about the problem*. Effective contextualisation includes describing the problem space, the objectives, and the desired format of the output. Participants reported that this contextual information improved the quality of output:

> *[...] if I give it more context about my problem then it gives me better answers [...] it also needs to be relevant context [...] How much context you need to give or not depends on what you're trying to do, but I think both the supplying of context as well as the approach or the methodological approach you ask it to follow to answer your query, those two things are probably the key aspects, I think. (P108)*

Related to context setting is *role specification*. A few participants mentioned that prompts could be improved by providing context about the role or persona that the GAI should adopt when responding to the query:

> *[...] you tell it "you're a world class copywriter and I need to communicate this" (P116)*

However, contextual information was only useful if it was relevant to the task being performed. Providing irrelevant contextual information could adversely affect the quality of the output provided by the GAI (P108, P114).

Participants (P108, P109, P113) also spoke about the need to use *the correct terminology* when prompting. Using the right terminology reduced ambiguity for the GAI and thereby resulted in better quality output. Another recommendation was using a '*step-by-step' prompt* as a way of improving the quality of the output (P108,

doi.org/10.32388/INFMMJ

P110). Breaking complex queries into manageable parts also allowed the user more control because they could see the steps taken by the GAI and modify them if necessary. Similarly, an *iterative approach* and testing modifications of prompts is required in order to improve the quality of the output, as noted by several interviewees (e.g., P108, P109, P110, P114, P116)

> *[...] it's definitely an iterative process because the AI, no matter how well you prompted and how well you explain the context, it still has the chance to just go off target. And so you've got to keep reminding it (P110)*

A few participants (P108, P118) noted that if the GAI repeatedly fails to produce the desired results, it was useful to *reset* and start the conversation from the beginning.

Another technique mentioned to improve prompting was using GAI to help generate prompts for later interactions. This ensures that the prompt is articulated in a way that enhances its understanding and execution, thus increasing the likelihood of getting the best output.

3.1.2. Making informed and responsible choices

Participants highlighted the importance of making informed and responsible choices about the use of GAI. They discussed safe and unsafe ways of using GAI, noting what information they share and where. They mentioned being careful not to *share sensitive or confidential data* with externally hosted GAI systems, contrasting this practice with what they regard as the approach of less effective users. Other participants spoke about considering how their queries are used and whether the data is sent back to developers and used to train the model. To use GAI well, users need to understand the IP and ethical issues that could arise as a result of using these tools.

> *ChatGPT itself [...] obviously learns from the inputs that you put into it. So, you would definitely not want to put anything that had IP or patient information in it (P121)*

Therefore, effective use of GAI means understanding the IP and ethical issues that could arise as a result of using these tools. A similar argument was raised by a participant who is an art teacher, who noted that more GAI-literate drawing students were thinking about the IP risks associated with GAI tools:

> *[...] a couple of my [students who are] really nice drawers are going 'Yeah, but what happens if I put my work up and then I see part of my work in a piece that's been generated?' (P109)*

Responsible use of GAI was also reflected in the way in which participants conceptualised their own roles and the role of the GAI. Many of our experts used terminology that reflected their awareness that they should be the responsible agent in the interaction, describing themselves as 'the one in charge' or 'in the driving seat'. In contrast, the GAI was described as an ‘assistant’, an ‘intern’, their ‘agent’ or a ‘tool’. Adopting this responsible stance meant that the user not only sets the task and guides the GAI, but also monitors its progress and is the one who would be conducting quality assurance to spot when the GAI was providing incorrect, flawed or incomplete output.

> *I show it something, ask it to give me feedback, I get feedback. I give it different feedback [...] It’s [...] a bit like how I manage my team. (P107)*

> *[...] it's my responsibility to check that it's accurate, in the same way that you would with a medical student (P121)*

Whether the GAI was described as an “assistant” or more like an equal or even higher collaborator (‘tutor’, ‘mentor’ and ‘colleague’), it reflects the various roles users envision GAI playing in their work. This highlights how GAI can alleviate some of the workload or provide guidance and offer feedback similar to a human counterpart.

Proficiency, as demonstrated by effective users, also involves making informed decisions about which GAI tools to use, when and how to use them, rather than using these tools arbitrarily. These decisions are based on their understanding of the functionalities of the various GAI tools and their respective strengths and weaknesses.

> *Most of my use is ChatGPT. And sometimes if I need Hebrew, I go to Claude. And if I need data that I'm going to dig into, [for] its links, I go to Perplexity [...] Perplexity is very convenient for this kind of academic research. Because all the data it gives you, it also gives you the links on which it is based. (P125)*

Using GAI tools appropriately, then, involves responsible use as indicated by safety considerations (what data to share and which tools to share it with), strategic decisions about whether GAI would be suitable for a task and if so, which GAI tool would be best, and finally, evaluating and where necessary, improving on the output of the GAI.

> *You need people who are going to take responsibility for the outputs (P112)*

3.1.3. Diversity of use: Tools and applications

Diversity of use refers to the variety of tasks and tools. Unlike the other two proficiency characteristics, this was not explicitly identified by participants as an indicator of proficiency. Instead, it emerged while reviewing descriptions of usage practices and noting differences in how and for what participants use GAI.

Most of the participants were mostly using popular GAI tools such as ChatGPT, CoPilot, Claude, Dall-E, or Midjourney, for relatively standard tasks like retrieving information, ideation, writing assistance (both generating text and reviewing it), summarising documents, generating images, coding assistance, and alike. Sometimes applications were used in combination to achieve improved output compared to what would be expected from using a single application, with different tasks being assigned to different tools.

> *[...] sometimes you'll use [...] multiple AI to get what you need as well. So crafting the perfect prompt using ChatGPT and then putting that into Midjourney. (P116)*

Fewer participants demonstrated a broader range of tools and tasks. They used more tools for more tasks and in more novel and complex ways, like screening datasets (P108, P112), creating mock data (P106, P130), or rostering (P121). The following is an example of how scientists use GAI to generate mock data with GAI to simulate and replace textual input that otherwise would have been provided by human participants.

> *... one of the more fun ones I did early on [...] where I was working on a controversial, disruptive technology [...], I said, "hey, can we have a town hall type discussion? Can we bring in, say, 5 stakeholders who are based around this disruptive technology and we can start this conversation," and it created like someone from the meat industry, someone from public health, someone from the public consumer, someone from lab supplies, and all this, and then, you know, a meat farmer as well (P106)*

The next use case was provided by a researcher specialising in design and technology. As part of his work, he often asks users to come up with stories about the technologies they wish to use, which serve as essential inputs for his work. However, in one of the projects within a highly specialised domain, the participants could not provide him with the desired stories. To address this gap, he used GAI to generate such stories instead of relying on his usual human users.

> *GenAI helps a lot when I have to develop rapid prototypes and tell a story about something very technical. So, for example, I'm working with a quantum chemistry team [...] and I want to tell a story about how a scientist is going to use their programming environment in the future. ...so, I was able to do it much more quickly than normal. So, because to tell this story, you need somebody who's imaginative and who understands the science domain and [...] who is willing to write a story about a person and be speculative? (P130)*

Occasionally, attempts to delegate tasks to the GAI fail, such as the rostering task mentioned by P121. Despite these occasional failures, these attempts show that proficiency also involves creatively pushing the boundaries of what can be achieved with GAI. It is the ideation and experimentation rather than the outcome. These novel complex tasks often involve solving intricate problems, compensating for limited resources (e.g., original data), or handling laborious tasks typically done by a team in a shorter time. Notably, these tasks are usually performed using coding tools rather than the standard chatbox interface, requiring specific expertise.

3.1.4. Usage frequency

Several users (P108, P111, P113, P115, P116, P120, P131) described using GAI often and embedding it into their regular, daily work practices. Some of these heavy, high-frequency users shared that the frequency of use has increased over time, which may reflect both the increasing capabilities of the technology and its ability to support users in their work, as well as the growing familiarity with these capabilities and knowing how to use them better for more tasks, as described earlier.

> *[...] when I first sort of started, I'd say it was more like it was a thing I did, whereas now [...] it's just part of my day now (P116)*

Like the diversity of use, frequency was not necessarily identified explicitly by the participants as a measure of proficiency. Yet, one participant did associate it with the level of usage:

> *high frequency users, they're starting to use the technology at a much more advanced level.*
>
> *At that advanced (level), [...] more creativity and innovative solving complex problems or coming up with new ideas to blah blah all that stuff. Whereas you know workers who just use it from time to time (P131)*

Only a couple of participants (P109, P121) reported using GAI at a lower frequency (several times a week or even less). When assessing how these participants use the AI, it seems that they were on the lower end of the diversity and complexity of use. It is possible, then, that there is an inner relation between frequency and diversity, indicating that frequency is another indicator of proficiency.

3.2. Competencies: knowledge, mindset, and skills

The primary objective of this study was to identify the core competencies that users utilised to effectively employ GAI tools and subsequently benefit from their use. In our framework, the competencies element is broken down into three categories: knowledge, mindset, and skills, in accordance with the acceptable categorizations[18].

3.2.1. Knowledge: GAI literacy

Participants emphasised the importance of understanding how GAI technology functions, including its strengths (e.g., interacting in natural language) and limitations (e.g., hallucinations). We label this competency as "GAI literacy" rather than "AI literacy" because participants focused on the specific features of

GAI rather than on AI in general (e.g., other types of AI such as computer vision or recommender systems). This understanding is crucial for effective usage and leveraging the technology's full capabilities. Participants argued that having an accurate comprehension of the technology and how it works (essentially, a calibrated mental model), rather than viewing it as a "magic box" (P110), allows users to adopt the right prompts and make informed decisions about tasks that the GAI can support. GAI literacy is necessary for the proficient use of GAI because it results in effective prompting and informed choices about when and how to use the tools. High GAI literacy involves being aware of the variety of GAI tools and their relative advantages and limitations, so that you can strategically select the best GAI tool for a given task, as the following quotes illustrate.

> *The first thing you have to do is use ChatGPT 4, use one that you pay for, and not the free one. That's a big difference because they're very different models. So the 4 is much bigger than the 3.5 (P106)*

> *[...] people should have at least some moderate amount of understanding of what's going on under the surface and don't just believe it's magic. [...] 'cause, [...] that helps you understand its limitations and why it sometimes gives you bad answers. And that helps you work through those situations when they do occur. Whereas if you just assume it's magic and can do anything, then [..] you're more likely to take it even when it's wrong (P112)*

> *[...] it's Claude which I prefer for more creative things rather than ChatGPT, and then I also use AI-generated image kind of production things [...] (P114)*

3.2.2. Knowledge: Domain expertise

Participants highlighted the paramount importance of having task-relevant knowledge, skills, and experience when using GAI. This 'domain expertise' was necessary both to "feed" or prompt the GAI and to assess its output. Domain expertise allowed users to provide appropriate contextual information, use the correct terminology, and provide relevant guidance, all of which helped to ensure that the output provided by the GAI would be appropriate and high-quality.

> *If you're looking for a certain style and you're not a graphic designer or something like that, there would be certain ways that they get a certain effect or they'd like, the different sort of design principles that would go into, like, good, powerful imagery and things like that. Like photographers would use, like, the Bokeh effect and those types of things. So having some domain knowledge definitely would give you better results. (P116)*

Second, domain expertise was necessary to evaluate the output of the GAI and identify if and how it could be improved.

 doi.org/10.32388/INFMMJ

I do have a lot of vet nursing knowledge in my brain, so when I'm looking at the answer that GPT is giving to me, I know exactly when the GPT is having hallucinations, so I can skip that out (P115)

I think I'm a dot-joiner, [...] in terms of my role and how I would use AI. I'm joining all these different dots and having that bird's-eye view and going 'OK, where does this fit?' and moving things around (P114)

We note here that applying domain expertise is a form of responsible use, as we mentioned earlier.

Likening the GAI to an "intern" (P114) or "junior" (P121), as noted earlier, also implicitly suggests that the human is the one who holds the expert role.

Domain expertise is necessary to transform the best or final output of the GAI into an acceptable deliverable, as noted by one of the interviewees from the legal field:

...when you edit it, you do get the more nuance, particularly with law, when you're really trying to explain nuanced risk to a client. I still think humans do that better than these models, just because you've got more context, more information, more knowledge about the client, personally, what they might want to have, where the tool is a, you know, just going off those documents and you know the large language model, which is [...] a predictive tool for predicting what word follows what next. So, I still think the human adds something to it without a doubt (P119)

3.2.3. Mindset: Curious, inquisitive mindset

Proficient use of GAI also appeared to be connected to users' mindsets. A few participants explicitly mentioned the importance of curiosity and inquisitiveness; many more mentioned it when describing how they approached GAI. It starts with a proactive approach of seeking out and testing new models as they became available. Then, curiosity and inquisitiveness are demonstrated in how one interacts with the technology. Many of our participants attributed their ability to prompt GAI effectively and use GAI in a wide range of ways to their inherent curiosity and motivation to learn and experiment with GAI. They described their engagement with GAI as playful, by which they discover more about the tools' capabilities, limitations, and applications (P106, P108, P109, P110, P111, P113, P114, P115, P116, P118).

It was so exciting getting into it, just playing around coding. So, I was playing around with

GitHub Copilot [... it] has just been jaw-dropping, [...] but it's just so much fun. [...] I was playing in that and then now with the copilot trial in that as well. Just getting the full exposure. (P118)

if you're curious [...] you'll naturally engage on a level where the questions will build on each other, and it'll build a much [...] richer conversation around that topic as you find areas of interests. This is the same sort of interaction. If [...] you approach it like you just want a solution to a particular problem or a

 doi.org/10.32388/INFMMJ

> *very quick answer, then you may as well do a web search because that'll give you the quick and dirty answer. [...]that's easy, but you're not learning from it as much. (P106)*

This curiosity and inquisitiveness are also evident in the frequency with which some of the participants described GAI knowledge-sharing practices that they engaged in. Participants were observing other users and discussing different approaches and strategies for various tasks with colleagues (P108, P109, P110, P114, P116). They were taking part in communities of practice, attending sessions with peers or experts (P108, P114, P116), and looking for information about GAI tools online (P108, P109, P110, P114, P116). Participants highlighted the importance of perseverance and investing time and effort in learning how to use GAI, emphasising that users who did not do so were risking failing to recognise the full value it offered.

> *You need to have a degree of playfulness or an experimentation to engage with these tools [...] I've found it curious how short people will be with this tool and go; 'it didn't give me a right answer. I'll never use it again. But if you hire a grad lawyer and they come up and give you a bad piece of work, you don't go oh, you're sacked the next day you would go. All right. What training do we need? How can I help you? What do I need to do? (P119)*

Only a few participants reported reaching a point of satisfying mastery using GAI; the majority described the learning process as ongoing, evolving, and open-ended. They noted that learning and knowledge sharing remained important even after becoming experienced users because the rapid evolution of technology required them to continually update their approaches and strategies in order to maximise the benefits of the tools:

> *So, I'm online a lot and getting information from a whole range of sources.*
> *and learning about different approaches fairly rapidly, even though [...] I know that they're changing, quite evolving [...]. There's no way to stay up to date with what's going on [...] there's always more, more to learn. (P108)*

> *But this it's changing so fast, like keeping up with everything you've got to learn can be a lot. So, I think you've got to be quite good at any updates and things like that that come like I find if I don't log in for a week, there's a whole new range of features that I didn't know about (P116)*

While exploration and curiosity were important in gaining proficiency, they should not undermine the importance of domain expertise, nor can they substitute for it. Engaging in exploratory practices without adequate domain knowledge may result in substandard or unsuitable output, as participant 121 explained:

> *Someone who isn't experienced that maybe could increase their game a little bit, the concern would be that reliance on it, whether it would steer you down an unknown bias, if you're relying on it too much*

‘cause, you're never quite sure of the data set that it's being trained on, are you suddenly gonna be diagnosing way more white male western diseases (P121)

3.2.4. Mindset: Flexibility, adaptability and creativity

Participants highlighted flexibility, adaptability, and creativity as essential qualities for effective use of GAI. Working with GAI necessitates multiple changes in one's approach to work, both cognitively and practically. It begins with the ability to shift one's mindset (essentially, mental models) about how the technology functions. When describing ineffective use of GAI, one participant said:

> *[...] the rigidity of how they [others – EG] work with the tool is quite one to one. They just have this very strong rigidity like "I need to click the button and get the output", [...] or "I want to navigate something in a very hierarchical manner", and this is the opposite of how a generative agent works. It is a very inaccurate tool if you are looking for a strong hierarchy. You're not going to input one and receive output two. You put input one in, and you get output A, B, C, D, and you can put the same input in twice and you get different outputs. (P124)*

The interviewee contrasted two distinct mindsets when working with GAI. The first is the “Hierarchical Approach”, which involves structured and linear thinking aimed at predictable and consistent output. The second, more suitable for GAI, requires the user to avoid the rigid expectation of consistent output and to be open to varied results each time.

Flexibility and adaptability are further evident in the ability to adjust to the frequent changes in GAI tools (i.e., the introduction of new applications and models with different, often enhanced capabilities).

> *And of course, it's evolving too. So, of course, I have to evolve with it. (P109)*

Adaptability was also seen to be important for proficient use of GAI because the evolving capabilities of GAI tools often demand changes to one’s work practices. Embedding the technology into tasks often requires new workflows, as the following participant explained:

> *It requires, on the one hand, a deep level of learning of new tools. And even more difficult is to get used to changes in the way you do things [...]. So, you already have habits, and you have beliefs, and you approach work in a certain way. (P125)*

Expert users are not only willing to integrate the technology as part of their workflow but also to reconceive their professional identity, including redefining their role, tasks, and responsibilities in this evolving landscape. P105 described changes in his and his team’s roles. He saw his own role as an editor, overseeing alternative design solutions suggested by his team and selecting the best ones. With the advent of GAI tools, his team members were shifting from being responsible for production to adopting more of an editorial role themselves:

> *...the work is entirely different; it is the work of editing. Essentially, the challenge for us today, as architects [...] is to find what interests us. It is not about creating it but finding it. [...] The guys here generate lots of alternatives, and I come and edit them, saying, "This has potential." [...] Now, in ten minutes, they can generate 100 options. But they can't show you all 100 options; so they [have to] differentiate among them. This is the editing process, selecting from what they see. Theoretically, if they are good, they pick the right ten, the interesting ten, and they become the editor [...]. They wrote something, asked the system for something, and it gave it to them, so they became the editors, presenting it to me as an edited version. (P105)*

Another adjustment described by some participants involved how they engaged with technology. While many still viewed technology as a “tool,” a significant number began referring to it using terms from teamwork, such as “teammate,” “colleague,” or “assistant” (as noted earlier). This anthropomorphic language indicates a mental shift toward a more collaborative approach with technology, allowing users to think differently about their tasks and how to manage them. They reconsider the division of work between themselves and their new technological partner, recognising the unique contributions of each. This shift is illustrated by the following quotes:

> *My expectation is that for a designer working with the generative tool that they would approach it like that...They would approach it as an agent that can collaborate with them on the kind of messiness of their ideas and their thinking and the back and the forth and the banter and the chat that they kind of have about what an idea could be and what it might be. (P124)*

> *All right, here's a task I would normally do it this way, but let's see how it can help. (P118)*

3.2.5. Mindset: Diligence

Diligence is another mindset that was raised by a few participants (P106, P112, P119, P126). Learning how to perform new tasks with GAI can be overwhelming, even for our participants. Less proficient users might give up when GAI doesn't assist effectively. Diligence in the context of working with GAI refers to the willingness to put in considerable effort while engaging with it. It is what supports the initial learning and later the iterative process that requires checking, tweaking, revisiting, and sometimes starting from scratch. It demands perseverance, endurance, and commitment to the process, rather than seeking quick gains. Our participants emphasised their readiness to invest the necessary time and effort, arguing that this patience and endurance distinguishes them from other users. One participant described his experience as follows:

That [image generation with GAI] worked well with a bit of tweaking like it's still took time but with a bit of tweaking it worked (P126)

Notably, when faced with a less familiar task that demanded a greater investment of time for learning, he was unwilling to commit, resulting in a different outcome:

I've tried. Well, I haven't succeeded. I've given up after little while I've asked it [...] I asked ChatGPT to tell me how to do it and it came up with full instructions and I've followed them and it didn't work in. Then I gave up so [...] I don't have expertise in creating plugins. I wasn't able to see why it didn't work and I couldn't fix it because I don't know enough about it. [...] the drawing [generated with GAI] was necessary, I needed it, but where's the plug in, this kind of a nice to have and I didn't know and the drawing I knew [...]. I'll get there eventually, but with the plugin I wasn't sure whether I would actually be able to finish it. But I'll just waste my time, so pulled the pin. (P126)

Attention to detail is another crucial virtue in this context. While GAI tools are appreciated for enabling users to complete their work more efficiently (i.e., with less time and effort), users cautioned against 'lazy' or 'complacent' use of these tools, as it can lead to subpar output.

You have to be diligent in assessing what it gives you and making sure that's right and true (P112)

3.2.6. Skills: Verbal communication skills

Communication skills (verbal expression, perspective taking, sharing information) were mentioned as something that effective users of GAI drew upon. Users with better communication skills would craft better prompts because they consider what information they should and should not provide, how to express themselves clearly, what expectations they needed to communicate (and in what order), and they naturally adjust the tone of their communication to fit the circumstances.

[...] they [the users] need to be [...] "personable" person, they need to be able to communicate effectively. And [...] be inquisitive, be able to extract information from people if needed. [...] they need to be able to talk to someone like a real person and be able to make that a meaningful process because if you can do that, then you can shift your thinking and talk to chatbots. (P110)

[...] for those people that speak out loud, you know, they may benefit way more from AI than someone who is quite introvert. (P121)

Notably, participants rarely limited communication skills to solely prompting. According to the interview data, effective communication skills also include the ability to organise one's thoughts and choose proper wording to clearly convey their ideas. In addition, communication skills mean perspective taking or taking an active

 doi.org/10.32388/INFMMJ

role to advance the dialogue. These verbal capabilities, which are often demonstrated in human-to-human interactions, are essential for crafting precise and effective prompts for GAI systems.

3.2.7. Skills: Critical thinking and metacognition skills

We noted earlier that a key aspect of proficient GAI use involves making responsible decisions. This includes choosing the appropriate tools, determining the suitable tasks for these tools, deciding what data to share, and reviewing and refining the output. These responsible decisions suggest that using critical thinking skills is important for proficient use of GAI. Other instances where critical thinking was seen to be important for proficient use of GAI were in assessing the GAI outputs and deciding the next step to be taken. When the process involves a combination of planning, monitoring, and reflection, it is often referred to as demonstrating "metacognitive skills". Hence, proficient use, as described in the previous section, inherently involves a metacognitive mindset. The following quotes illustrate how participants conceptualised the role of metacognition and critical thinking in supporting prompting and output evaluation:

> *[...] a couple of times I've caught myself going and doing things and I'm like, "no, no, no. I should ask the AI this because this is a waste of my time". [...] that kind of recognition and creativity around what problem am I trying to solve. [...] what am I trying to do, like stepping back and then thinking about, 'OK, what are some creative questions or maybe creative approaches? [...] Where can I start to crystallise these ideas with an AI, how can I start to ask the right questions to bring it together into something concrete' (P113)*

> *It's a kind of critical thinking [...] approach that you go to when you're trying to –[...] analyse what someone else is saying and understand why they're thinking that [...] You have to kind of come up with ideas for why that particular output was generated. Different hypotheses. And then it's trial and error, right? If I tweak these, does that work? (P111)*

> *[...] that critical thinking of: Is that the answer to the question I asked and is it quite what I wanted? You've constantly got to be going through that with the AI as well. (P112)*

3.2.8. Skills: Information technology skills

There appeared to be an association between users' information technology skills (programming skills in particular) and their ability to use GAI in complex and novel ways. Importantly, none of the participants stated that information technology skills were required for proficient use of GAI. Nevertheless, programming and coding skills seemed to underpin the more complex and novel uses of GAI and achieve more creative outputs. For example, participants with programming skills described using APIs and endpoints to integrate GAI capability within other systems.

Nevertheless, it is important to note that technical skills are not a prerequisite for achieving quality output. Relying on other competencies can also lead to high-quality results, as indicated by a medical doctor:

> *a bunch of people [physicians – EG] who had really struggled to get a diagnosis between a load of specialists for like 9 months and they kind of sat down [...] they basically asked it a series of questions and it got it within like few things. And [...] these are specialists that are autonomous [...] people. And it just joined the dots together that no one else specifically had and none of them were probably particularly tech savvy. (P121)*

3.3. Benefits

The third element in our framework highlights the outcomes achieved from proficiently working with GAI tools. In this section, we describe the types of benefits that were seen to flow from being a proficient user of GAI tools, drawing out how different competencies and facets of support better outcomes. Two broad themes emerged from the interviews when participants described the gains that were achieved by effective GAI use. One theme related to productivity or efficiency, and the other theme to the quality of the output produced when working with GAI, including accuracy and novelty.

3.3.1. Productivity and efficiency

Participants mentioned time savings, increased efficiency, and improved productivity as the main benefits of working with GAI.

> *...teachers are time poor. So, if I can get some new content coming in to make it more relevant to students right now, that's a bonus for me, [...] But because we're time poor, we don't get that [team brainstorming] anymore. So, I'm using ChatGPT to actually kind of do that for me now. (P109)*

> *So I said to Claude, "take all this data from the Excel spreadsheet. Refer to Kirkpatrick's levels of learning evaluation and basically find patterns in what I've uploaded". And it did it. In 10 seconds. But it would have taken me... it would have taken me at two months, three months to do it... (P114)*

However, participants illustrated a range of ways that these productivity gains could be compromised when the tools were used less proficiently. Two participants described how their GAI literacy allowed them to avoid wasting time giving tasks to the GAI that it wouldn't do well:

> *To understand how it works, what it is good at and what it is not good at will save you lots of time. You know there are tasks you do in Photoshop, and you don't need the AI for that, and other tasks, you know it'll help you, so you already know what to do and how to do it. (P104)*

doi.org/10.32388/INFMMJ

One participant (P104) also made a link between an artist's domain expertise, the quality of the artist's prompts, and the level of productivity that the artist could achieve when using GAI tools:

> *[...] It's a sketch [of a painting] that you make very quick, something like fifteen minutes for a skilled artist. And then [the artist] puts it through the model and also describes the character, the design language, the style and it becomes that in a matter of minutes. (P104)*

Another person explained how his domain expertise allowed him to be efficient in directing and validating the output that he got from GAI and therefore more productive when using GAI in his field of expertise:

> *[...] it's knowledge, it's understanding what you're trying to achieve and the information that you're putting in. So, because [...I have] a really good knowledge background in the areas of history that I teach, when you run something through Chat[GPT], you almost know instantly if it's accurate or not, and that I think that really, really helps. (P129)*

Metacognition (planning, reflecting) was also important for productivity in that reflection allowed users to identify when a task or specific aspect of a task could be done more efficiently with the assistance of GAI.

3.3.2. Quality improvement

When used well, GAI also improves the quality of users' work. However, maximising the quality improvements gained from using GAI was clearly connected to specific aspects of proficiency. First, crafting 'good' prompts was a means of obtaining output that was better aligned with one's objectives or more relevant to the problem.

> *in terms of labour cost, we should reduce that labour cost very simply, like that's very straight forward as long as the quality is the same and it is the case that if you can have prompt it effectively you can achieve comparatively similar quality for lots of contexts. (P124)*

The following quote illustrates how one participant connected experimentation (a competence), conversational and iterative prompting (a proficiency), and achieving a more creative solution while using GAI (benefit):

> *... the end advice that you get out of using advice generator is a collaborative sort of output. So you know, it's not producing the final product, but you are taking answers from it, putting it in, adding your text, asking it further questions, querying data, and then between the two of you, you end up sort of generating the text that goes into an advice. (P119)*

Metacognition –– also facilitated informed and responsible decisions about the use of GAI tools, thereby reducing the likelihood of poor outcomes:

[...] So obviously you know a lot of people are using AI, including myself, to get work done more productively, faster, save time. Then you don't take the time to reflect. Did this work? Was it ethical? Did it do the job well? [...] what can I do better? So having that self-reflection ...(P114)

GAI literacy was also connected with the quality of output. Being aware of the potential for tools to hallucinate and therefore taking the time to validate information provided by GAI tools was important to ensure that one's work was accurate and well-grounded.

you still have to go back and make sure that it's correct as well, though. So, you have to, yeah, it could generate it in in three or four seconds. Yes. But then I have to go in and go. OK, I've now got to look at those artists and look at what it said and go, OK, is that correct? Do the research [...] (P109)

Responsible choices (e.g., investing additional effort to ensure the output was aligned with a client's requirements) were also important to achieve high-quality output when using GAI tools:

Diversity of use (using GAI for a wider range of tasks and across multiple stages of work) was important to maximise the quality of work. Using GAI across stages from ideation to content generation, to editing, to adapting provided a wider range of ways of improving quality. As participants explained, GAI could be used to support brainstorming and thereby generate more ideas about how to approach a problem:

[...] to get other ideas just to sort of spark that kind of different ways of thinking about things [...] (P111)

Alternatively, used as a research tool, GAI would provide more information to draw upon when developing a solution or making a recommendation:

[Doing] the research [...] that's when I kind of go [...] That's good. I know all that that's already in there. I've got it. Thank you. But [...] cherry-picking those bits that I hadn't thought of, or I hadn't realised it was out there as well. (P109)

Used at the editing stage, GAI allowed users to identify weaknesses or additional improvements that they would not have noticed otherwise:

... I've kind of produced the material and put it into GAI and asked it to give me feedback on it: 'Take what I've done and work towards a very specific goal'. And that goal was structured in a way that the information was in the database [...] So it was able to look at what I produced relative to the material that was available to it and in its database and say, 'you haven't done this, you haven't done that, you've got to put this in, that bit's missing'. (P123)

Understanding the strengths and weaknesses of different GAI tools (i.e., GAI literacy) and using a variety of them can result in higher quality outcomes. Participants explained that they would prefer a specific GAI tool

doi.org/10.32388/INFMMJ

for a particular task because it delivers higher quality output for that task.

> *I'm using Copilot and GPT, but Copilot is not the same as GPT, so GPT is for me the questions that are asked. A Copilot is more like 'Here are the resources. Let's work on that'. It's just we're talking about two different tools (P115)*

Finally, although it was not stated explicitly, participants' descriptions of more complex and novel ways in which they were using GAI tools appeared to result in higher value services or products.

> *We are hoping this [...] help [the grad lawyers] move up the value chain [...] So rather than them doing document reviews and [...] some of the more boring legal tasks than just [...] summarising and typing, they can get that done quickly and then get on to the more creative side of being a lawyer, which is really thinking about what your client problem really is and how to solve it (P119)*

4. Discussion

To the best of our knowledge, this study represents the first to comprehensively and empirically explore and define the proficiency of using GAI and its underpinning competencies. Analysing in-depth descriptions of GAI use provided by 25 expert users revealed a broad set of skills, knowledge, and mindsets that were seen to support productivity, quality, and originality when working with GAI tools. Furthermore, these competencies emerged repeatedly, although we interviewed knowledge workers who were working in a range of roles and sectors. In popular discourse, prompt engineering[24] and awareness of hallucinations[42] have dominated discussions about effective use of GAI. Our research suggests that these aspects of proficient GAI use, labelled as effective prompting and informed and responsible choices, are the product of (mostly) traditional competencies, ranging from domain expertise to communication skills to diligence.[24][42] Although some of these competencies have been (individually) identified by other researchers[38][14][43][8][36][44][45] as potentially important for GAI use, the broad focus of our study enabled us to develop a comprehensive framework of effective GAI use which delineates the combination of skills, knowledge, and mindsets required for effective GAI use and the different facets of GAI proficiency that collectively contribute to the productivity, quality, and original outcomes sought from GAI use.

The GAI competency framework identifies four behavioural indicators of proficient GAI use: effective prompting, making informed and responsible decisions, diversity and complexity of use, and frequency of use. The importance of prompting is widely acknowledged[23][11][24][25][26][46][26]. There is also prior research attesting to response choices such as verifying output, sharing data carefully, and remaining accountable for the quality of work produced when working with GAI tools[11][47][48]. The third aspect of proficiency, diversity and complexity of use, is less commonly mentioned, but there is a growing body of evidence attesting to the

doi.org/10.32388/INFMMJ

potential for GAI to be used across multiple types of tasks and in multiple stages of one's workflow[7][5]. He et al.[49] reported that the complexity of the task affects participants' preferences for the automation interface. Future work could investigate whether diversity and complexity of GAI use improve with training.

The competencies identified in our framework (GAI literacy, domain expertise, communication skills, metacognition skills, curiosity and inquisitiveness, flexibility and adaptability, diligence, and information technology skills) are also supported by prior research. The two knowledge elements that support proficient use of GAI, as identified from the interviews, are GAI literacy and domain expertise. *GAI literacy* refers to having (some) familiarity with the principles of the underlying models and the specific applications in the fields and being aware of their limitations and strengths in a way that guides effective prompting and responsible use. We view GAI literacy as a form of AI literacy since it is also associated with the ability to understand, use, and assess the ramifications of AI tools[30][32][33]. However, participants emphasised the importance for GAI users to understand which types of GAI tools were suitable for specific tasks and to recognise their strengths and weaknesses. They did not assert that proficient GAI use required an understanding of other commonly used forms of AI.

Domain expertise, defined as task-relevant knowledge, skills, and experience, is crucial for productive, high-quality output. It supports effective prompting by enabling users to provide relevant context, appropriate terminology, and to guide the GAI towards high-quality responses. It also ensures informed, responsible use by enabling users to evaluate what information should (and should not) be shared with the GAI, whether the GAI's output is appropriate, and how it could be improved. Other researchers[38][8][50][44] have also highlighted the pivotal role of domain expertise in ensuring and enhancing output produced with GAI tools. Moreover, the importance of human domain expertise for achieving productive and high-quality output supports the argument that the latest developments in AI serve to augment rather than to simply replace human workers[51][52]. Einola & Khoreva[53] argue that balancing between delegating tasks to GAI and capitalising on human expertise is a challenge that human workers now have to negotiate. We contend that domain expertise maintains the delicate balance between overseeing the GAI's tasks and completely delegating responsibilities to GAI tools. Future research could assess the level of expertise required to provide independence to non-expert users while maintaining the quality of the output. It is intriguing to consider whether GAI can be used for specialized, knowledge-intensive tasks currently performed by experts. Additionally, to what extent can novice professionals (such as teachers, designers, or modelers) with good prompting skills produce and guarantee high-quality output comparable to experts in these fields? Should we trust a GAI-derived analysis requested by a non-expert professional? At this stage, we do not have definitive answers to questions relating to the implications of using GAI by non-experts in terms of the quality of deliverables.

Our findings also show the importance of users' mindsets in supporting proficient GAI use. Our participants emphasised the need for curiosity, experimentation, and continuous learning to effectively use GAI. Although this finding could be attributed to the relative infancy of GAI (or the hype around it), participants argued that the constant evolution of GAI tools and the frequent introduction of new GAI tools mean that curiosity and learning will remain important for proficient GAI use. This inquisitive kind of approach reflects a "growth mindset" - "the belief that intelligence is not fixed, and that performance can be improved through effort, good learning strategies, and mentoring and support from others"[17]. A growth mindset is positively related to innovative behaviour[54], which may explain the observable connection between expert users' curiosity and investment in learning and their ability to use GAI in more complex, diverse, and novel ways than less proficient users. The importance of curiosity and experimentation in driving technology usage is supported by many studies relating to the adoption of technology in general and the adoption of AI in particular[55][5].

Adaptability and diligence are other necessary mindsets for effective use of GAI, given the evolving capabilities of GAI tools. Ongoing technological improvements mean that users need to continually adjust their thinking about their roles and work processes. Microsoft's report[5] found that power users have reoriented their work patterns in fundamental ways and are 66% more likely to redesign their business processes and workflows with AI. These findings align with the notion that adaptability is required for proficient GAI users.

However, being adaptable and willing to delegate tasks to the AI should not mean handing over all responsibility. A few interviewees explained that maintaining a diligent mindset is important because GAI tools could unintentionally encourage laziness. The tools often perform reasonably well, which may create a false sense of unquestionable reliability and an inclination to maximise speed and productivity by relying on the GAI without verifying its output. To achieve high-quality output, users need to be aware of potential complacency and act responsibly by staying vigilant. Hence, a diligent mindset is important to support the perseverance, attention to detail, and willingness to invest time and effort when working with GAI tools. The importance of diligence is also suggested in the Microsoft[5] study of GAI 'power users,' where the authors reported that power users were differentiated by their willingness to keep trying in order to achieve an optimal response from GAI rather than a 'good enough' response. The positive direct and indirect relationship between diligence and performance has been demonstrated in other studies[56][57][58][59].

In the skills category, verbal *communication skills* were often highlighted as an important ability given the conversational nature of GAI. These communication skills go beyond just adopting a conversational language (as opposed to a computational or programming language). Instead, they were described as involving the abilities to effectively construct a conversation, clearly articulating users' ideas (i.e., prompts) or providing explicit instructions to guide. These are core elements that sometimes less proficient users miss[25].

In addition, the importance of *metacognition* and critical thinking emerged from the analysis. Similar descriptions of best practices are reported in the Microsoft report of power GAI users. Further, Robertson et al. [26] argue that "the backbone of prompt engineering entails thoroughly thinking through the process of how to construct the problem, opportunity, or question that you are posting to the GenAI tool." Researchers (e.g., Sidra & Mason[36]; Yan et al.[45]) argue that metacognition skills will be especially important when collaborating with AI because many of our cognitive heuristics become dysfunctional when they are used with AI. They also argue that since AI is not self-aware, the provision of this higher-level cognitive awareness and regulation will form part of the human worker's AI-complementary skills.

Finally, although participants did not explicitly mention it, we recognise the importance of information technology skills as a GAI competency. Our findings suggest that participants with a background in information technology utilised GAI tools in more complex and innovative ways. Despite most GAI tools operating through natural language and an easy-to-use interface, having knowledge of information architecture and programming allows users to integrate GAI tools into other systems, thus enabling more sophisticated and inventive tasks and eventually more creative output and obtaining greater value from these systems.

Many of the GAI competencies that we identified form part of what are commonly referred to as "21st century skills" or "digital skills"[60][61] and are considered highly desirable skills. For example, the top 10 skills of 2023 according to the World Economic Forum[62] are analytical thinking (ranked #1), creative thinking (#2), resilience, flexibility and agility (#3), curiosity and lifelong learning (#5). Technological literacy (#6), attention to detail (#7), active listening (a form of communication skills, #8) and quality control (#10). The first five competencies also appear on the list of top 10 skills on the rise, with some ranking differences[62].

In relation to benefits, our findings support a large body of literature showing that the primary benefit and motivation for using GAI is increased efficiency and productivity, allowing users to accomplish more work in less time[63][10][39][8]. GAI proficiency also contributes to the quality of the work by increasing accuracy and creativity, as reported by others[10][39][10][39]; however, our findings indicate that improvements could also lead to delivering novel sets of outcomes (i.e., expanding the range of deliverables, like e.g., new analyses, new services and alike). New outcomes could be achieved either directly by utilising GAI to create new outputs or indirectly by freeing experts to focus on more innovative work. Thus, effective use of GAI could go beyond merely increasing productivity and speed, assisting users in rethinking and expanding their deliverables.

There is a question remaining, though, about the relationship between proficiency and novelty of the outputs, which is worth further investigation. Furthermore, the interactions between the three high-level categories (e.g., establishing how competencies are related to different facets of proficiency or how proficiency is associated with different benefits) are beyond the scope of this research and should be a part of future

doi.org/10.32388/INFMMJ

research. The relationship between competencies and performance (whether indicated by proficiency or benefits) is fairly established in the literature. Specifically, research has shown connections between elements reported here. For example, it was shown that better prompting skills predict better output (benefits)[25]. Based on our findings, we believe that the benefits of productivity and quality are achievable with some proficiency, as demonstrated in effective prompting and responsible use. However, it is expected that as the capabilities of GAI and its adoption increase in the future, knowledge workers might need to develop additional facets of proficiency. This includes leveraging GAI in innovative ways and integrating it more deeply into their workflows to add value in new and diverse ways.

4.1. Limitations

Our findings are based on the input from 25 expert GAI users, whose expertise was subjectively assessed by others and may not reflect objective measures. Furthermore, we observed variability in expertise levels, likely due to domain-specific differences rather than individual differences. Further research should rigorously examine the expertise to validate these observations.

We adopted an in-depth and focused approach to gain detailed insights into the competencies and behaviours that differentiate effective and ineffective GAI use. However, further research is needed to capture a wider range of input and establish the generalisability of our findings.

A potential criticism of our findings (especially those pertaining to the importance of curiosity and adaptability) is that they could reflect the fact that this study was carried out in an early stage of GAI technology adoption. Until OpenAI launched in November 2022, relatively few technology experts were aware of GAI technology. Most of our expert users had only been using GAI to support their work since ChatGPT was first introduced (15 months on average). Some of the attributes that our experts shared may indicate more about their early adopter characteristics rather than experts' GAI requirements. However, even within our small sample of early adopters, variability in proficiency was observable and could be linked with one or more of the GAI competencies.

Another limitation is that over time, the range of applications and the use of GAI tools may stabilise, and we may note changes in the relative importance of different competencies. For example, adaptability and curiosity may become less critical for proficient GAI use. It is possible that some of the competencies our experts considered important are sensitive to the rate of technology adoption or its maturity.

Therefore, a further study is required to assess whether these competencies are time-sensitive.

4.2. Directions for further research

Our research findings offer several directions for further research. First, future research is needed to confirm and refine the observed constructs of competencies, proficiency, and benefits of GAI use, along with their attributes and interrelations. Further research is needed to probe the relationships within and between these categories (e.g., to establish whether specific competencies or specific proficiencies are important for certain types of outcomes). Further research is needed to test the generalisability of our findings. For example, in our study, we focused on knowledge workers who were expert users of GAI tools. In roles where workers have less autonomy, the complexity and novelty of GAI use may be less important for the effective use of GAI tools.

Another important focus for further research relates to our finding that GAI literacy (rather than AI literacy) is important for proficient use of GAI tools. Given the level of investments being directed by governments, corporates, and individuals towards AI upskilling[64][65][66][67], it will be important to test whether AI literacy or GAI literacy interventions are effective in supporting users to maximise the benefits of GAI tools. In addition, this study suggests that effective prompting is associated with personal communication skills. Delineating what types of communication skills are needed from GAI and what aspects of communication GAI can augment will be important to align educational offerings with future skills needs.

Further research should compare the perspectives and performance of domain experts, novices, and laypersons to confirm the importance of domain expertise for proficient use of GAI tools and for producing high-quality outputs. Such research could investigate whether novice workers who are also "GAI natives" are capable of achieving sufficient quality despite their lack of domain expertise. Another issue deserving further research relates to how novice workers develop the domain expertise they need to work effectively with GAI tools. Our research participants were all experienced workers with sufficient depth of knowledge to quickly identify gaps and inaccuracies in the GAI output. Although our participants were generally enthusiastic about the use of GAI, they were concerned that workers who join the workforce now (at a time when GAI use is increasingly ubiquitous) will not develop the ability to independently evaluate the GAI output. There is already some research suggesting that excessive reliance on GAI tools affects learning[68][69][70][45]. Research is needed to determine whether novice workers gain the domain expertise required to use GAI responsibly and effectively if they work in an environment where GAI tools are in regular use and what strategies ensure that humans remain the primary agents of critical thinking and problem-solving[45]. Such research is needed to inform approaches to career development in an era when GAI tools are used across learning and work environments.

Lastly, further study is required to determine if these competencies are tied to the technology's life cycle stage or are independent of its adoption rate and maturity.

4.3. Practical implications

Our study offers practical guidance for educators, employers, workers, and students by providing a grounded and comprehensive framework for working with GAI effectively. While prompt engineering and awareness of GAI's potential to hallucinate are commonly discussed aspects of proficiency, our research expands the concept of proficiency and reveals its underlying competencies. These competencies can reinforce effective and beneficial use of GAI that will result in new and better products and services, rather than merely efficiency gains. The importance of curiosity, experimentation, and diligent mindsets in achieving more gains suggests that workplace culture and reward systems might play a vital role in supporting workers who use GAI (while ensuring countermeasures to avoid the complacency effect).

There is a valid concern that despite the awareness of the weaknesses of GAI tools, high workloads and deadlines may push workers to over-rely on the GAI output without adequate examination. In addition, some are unlikely to find the time to experiment and discover novel uses for GAI. Therefore, workplaces should move beyond merely introducing GAI tools to their employees or offering single training sessions, such as in prompting strategies. It would be more beneficial for organisations to establish communities of practice and encourage employees to participate in order to ensure ongoing knowledge sharing. Additionally, organisations could encourage employees to rethink their work processes and explore new possibilities for working with GAI. However, maintaining proper checks to avoid over-reliance on the technology is crucial.

5. Conclusion

This study identifies the key competencies and expertise necessary to maximise the productivity and quality benefits of GAI tools. We have confirmed that GAI proficiency is reflected in users' prompting skills and responsible use, as often discussed in the academic literature as well as in the public discourse. However, we showed that proficiency is also indicated in what users do with the GAI, the diversity and complexity of the tasks they delegate to the GAI, and how they utilise the various GAI tools available. Additionally, we emphasised that gaining GAI proficiency requires honing a diverse set of knowledge, skills, and mindsets. While further validation is required, this framework represents a significant advancement in offering the guidance and detail that individuals, employers, trainers, and policymakers need to successfully navigate the GAI-enhanced work environment.

Acknowledgments

We extend our heartfelt gratitude to our colleagues for their invaluable contributions to this research. Special thanks go to Alexandra Bratanova, Scott Spillias, and Simone Felton for their thorough review and insightful suggestions, which have significantly enhanced the quality of this work. We also deeply appreciate Cecile Paris and Andrew Reeson for their continuous support and encouragement throughout the project. Furthermore, we are grateful to Sidra, Phoung Anh Tran, Sichen Meng, and Yijing Liao for the constructive discussions along the way. Lastly, we acknowledge the support of the CSIRO Collaborative Intelligence (CINTEL) Future Science Platform.

References

1. ^*Ebert C, Louridas P (2023). "Generative AI for Software Practitioners." IEEE Software. 40(4): 30–38. doi:10.1109/MS.2023.3265877.*
2. ^*Bhattacharya P, Prasad VK, Verma A, Gupta D, Sapsomboon A, Viriyasitavat W, Dhiman G (2024). "Demystifying ChatGPT: An In-depth Survey of OpenAI's Robust Large Language Models." Archives of Computational Methods in Engineering. doi:10.1007/s11831-024-10115-5.*
3. a, b*Singla A, Sukharevsky A, Yee L, Chui M, Hall B (2024). The state of AI in early 2024: Gen AI adoption spikes and starts to generate value.*
4. ^*Peres R, Schreier M, Schweidel D, Sorescu A (2023). "On ChatGPT and beyond: How generative artificial intelligence may affect research, teaching, and practice." International Journal of Research in Marketing. 40(2): 269–275. doi:10.1016/j.ijresmar.2023.03.001.*
5. a, b, c, d, e*Microsoft. (2024). 2024 Work Trend Index Annual Report. https://assets-c4akfrf5b4d3f4b7.z01.azurefd.net/assets/2024/05/2024_Work_Trend_Index_Annual_Report_663d45200a4ad.pdf*
6. ^*Gupta P, Ding B, Guan C, Ding D (2024). "Generative AI: A systematic review using topic modelling techniques." Data and Information Management. 8(2): 100066. doi:10.1016/j.dim.2024.100066.*
7. a, b*Irons J, Mason C, Cooper P, Sidra S, Reeson A, Paris C (2023). Exploring the Impacts of ChatGPT on Future Scientific Work. doi:10.31235/osf.io/j2u9x.*
8. a, b, c, d, e*Noy S, Zhang W (2023). "Experimental evidence on the productivity effects of generative artificial intelligence." Science. 381(6654): 187–192. doi:10.1126/science.adh2586.*
9. ^*Choi JH, Schwarcz D (2023). "Ai assistance in legal analysis: An empirical study." Available at SSRN 4539836.*
10. a, b, c, d*Brynjolfsson E, Li D, Raymond L (2023a). Generative AI at Work. arXiv. doi:10.48550/ARXIV.2304.11771.*
11. a, b, c, d, e, f*Dell'Acqua F, McFowland E, Mollick ER, Lifshitz-Assaf H, Kellogg K, Rajendran S, Krayer L, Candelon F, Lakhani KR (2023). "Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality." SSRN Electronic Journal. doi:10.2139/ssrn.4573321.*
12. a, b*Williams R, Fletcher C (2002). "Performance Management and Organizational Effectiveness". In Organizational Effectiveness. pp. 135–158. doi:10.1002/9780470696736.ch6.*
13. ^*Bartram D, Robertson IT, Callinan M (2002). "Introduction: A Framework for Examining Organizational Effectiveness." In Organizational Effectiveness (pp. 1–10). doi:10.1002/9780470696736.ch.*

14. [a, b]Hlavac J (2023). "Knowledge, skills and abilities (KSAs) as a metric to re-conceptualise aptitude: a multi-stakeholder perspective." The Interpreter and Translator Trainer. 17(1): 29–53. doi:10.1080/1750399X.2023.2170052.
15. [^]Brynjolfsson E, Li D, Raymond LR (2023b). Generative AI at work. National Bureau of Economic Research.
16. [^]Cui KZ, Demirer M, Jaffe S, Musolff L, Peng S, Salz T (2024). "The Effects of Generative AI on High Skilled Work: Evidence from Three Field Experiments with Software Developers." SSRN. https://ssrn.com/abstract=4945566.
17. [a, b]Dweck CS, Yeager DS (2019). "Mindsets: A View From Two Eras." Perspectives on Psychological Science. 14(3): 481–496. doi:10.1177/1745691618804166.
18. [a, b, c]Gottfredson RK, Reina CS (2021). "Illuminating the foundational role that mindsets should play in leadership development." Business Horizons. 64(4): 439–451. doi:10.1016/j.bushor.2021.02.009.
19. [^]Deans DH (2024, July 13). "Executive Guide to Generative AI Prompting." Medium. https://medium.com/technology-media-telecom/executive-guide-to-generative-ai-prompting-b91669c5d3c9#:~:text=At%20the%20core%20of%20interacting%20with%20Generative%20AI, improved%20results%20across%20a%20wide%20range%20of%20tasks..
20. [^]Eliot L (2024, May 9). "The Best Prompt Engineering Techniques For Getting The Most Out Of Generative AI." Forbes. https://www.bing.com/ck/a?!&&p=f35fe42f1f0626f939fafbb306eda4b6b837b7ba3e356041fc158edf6afd11d7JmltdHM9MTczNjY0MDAwMA&ptn=3&ver=2&hsh=4&fclid=26a29942-fd56-6b2a-16b9-8c2ffc836a05&psq=The+Best+Prompt+Engineering+Techniques+For+Getting+The+Most+Out+Of+Generative+AI&u=a1aHR0cHM6Ly93d3cuZm9yYmVzLmNvbS9zaXRlcy9sYW5jZWVsaW90LzIwMjQvMDUvMDkvdGhlLWJlc3QtcHJvbXB0LWVuZ2luZWVyaW5nLXRlY2huaXF1ZXMtZm9yLWdldHRpbmctdGhlLW1vc3Qtb3V0LW9mLWdlbmVyYXRpdmUtYWkv&ntb=1.
21. [^]Wilson HJ, Daugherty PR (2024). Embracing Gen AI at Work. Magazine (September–October 2024). https://hbr.org/2024/09/embracing-gen-ai-at-work
22. [^]Zhou Y (2023, December 12). AI Prompting: The Universal Skill for the Next-Gen Workforce. Medium. https://medium.com/generative-ai-revolution-ai-native-transformation/ai-prompting-the-universal-skill-for-the-next-gen-workforce-c800f1a11064
23. [a, b]Dang H, Mecke L, Lehmann F, Goller S, Buschek D (2022). "How to Prompt? Opportunities and Challenges of Zero- and Few-Shot Learning for Human-AI Interaction in Creative Applications of Generative Models." ArXiv. abs/2209.01390. https://api.semanticscholar.org/CorpusID:252089610.
24. [a, b, c, d]Denny P, Leinonen J, Prather J, Luxton-Reilly A, Amarouche T, Becker BA, Reeves BN (2024). "Prompt Problems: A New Programming Exercise for the Generative AI Era." Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1. 296–302. doi:10.1145/3626252.3630909.
25. [a, b, c, d]Knoth N, Tolzin A, Janson A, Leimeister JM (2024). "AI literacy and its implications for prompt engineering strategies." Computers and Education: Artificial Intelligence. 6: 100225. doi:10.1016/j.caeai.2024.100225.

26. a, b, c, d Robertson J, Ferreira C, Botha E, Oosthuizen K (2024). "Game changers: A generative AI prompt protocol to enhance human-AI knowledge co-construction." Business Horizons. 67(5): 499–510. doi:10.1016/j.bushor.2024.04.008.
27. a, b Zamfirescu-Pereira JD, Wong RY, Hartmann B, Yang Q (2023). "Why Johnny Can't Prompt: How Non-AI Experts Try (and Fail) to Design LLM Prompts". Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems. doi:10.1145/3544548.3581388.
28. ^ Boscardin CK, Gin B, Golde PB, Hauer KE (2024). "ChatGPT and generative artificial intelligence for medical education: potential impact and opportunity." Academic Medicine. 99(1): 22–27.
29. ^ Brandão A, Pedro L, Zagalo N (2024). "Teacher professional development for a future with generative artificial intelligence–an integrative literature review." Digital Education Review. 45: 151–157.
30. a, b, c Chandra P, Dubey A, Sharma SK, Karsoliya S (2024). "A novel Conceptualization of AI Literacy and Empowering Employee Experience at Digital Workplace Using Generative AI and Augmented Analytics: A Survey." Journal of Electrical Systems. 20(2): 2582–2603. https://www.proquest.com/scholarly-journals/novel-conceptualization-ai-literacy-empowering/docview/3074172539/se-2?accountid=26957.
31. ^ Putjorn T, Putjorn P (2023). "Augmented Imagination: Exploring Generative AI from the Perspectives of Young Learners." 2023 15th International Conference on Information Technology and Electrical Engineering (ICITEE), 353–358. doi:10.1109/ICITEE59582.2023.10317680.
32. a, b Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 1–16.
33. a, b Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. Computers and Education: Artificial Intelligence, 2, 100041.
34. ^ Hornberger M, Bewersdorff A, Nerdel C (2023). "What do university students know about Artificial Intelligence? Development and validation of an AI literacy test." Computers and Education: Artificial Intelligence. 5: 100165. doi:10.1016/j.caeai.2023.100165.
35. ^ Spector JM, Ma S (2019). "Inquiry and critical thinking skills for the next generation: from artificial intelligence back to human intelligence". Smart Learning Environments. 6(1): 8. doi:10.1186/s40561-019-0088-z.
36. a, b, c Sidra, S., & Mason, C. (2024). Reconceptualizing AI Literacy: The Importance of Metacognitive Thinking in an Artificial Intelligence (AI)-Enabled Workforce. 2024 IEEE Conference on Artificial Intelligence (CAI), 1181–1186.
37. ^ Jarrahi MH (2018). "Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making." Business Horizons. 61(4): 577–586. doi:10.1016/j.bushor.2018.03.007.
38. a, b, c Annapureddy R, Fornaroli A, Gatica-Perez D (2024). "Generative AI Literacy: Twelve Defining Competencies." Digital Government: Research and Practice. doi:10.1145/3685680.

39. ^a, b, c, d, e^ *Cardon P, Fleischmann C, Logemann M, Heidewald J, Aritz J, Swartz S (2024). "Competencies needed by business professionals in the AI age: Character and communication lead the way." Business and Professional Communication Quarterly. 87(2): 223–246. doi:10.1177/23294906231208166.*
40. ^a, b^ *Charmaz K (2008). "Grounded theory as an emergent method." Handbook of Emergent Methods. 155: 172.*
41. ^ *Lumivero. (n.d.). NVivo12.*
42. ^a, b^ *Pinski M, Benlian A (2024). "AI literacy for users – A comprehensive review and future research directions of learning methods, components, and effects." Computers in Human Behavior: Artificial Humans. 2(1): 100062. doi:10.1016/j.chbah.2024.100062.*
43. ^ *Levenson AR, Van der Stede WA, Cohen SG (2006). "Measuring the Relationship Between Managerial Competencies and Performance." Journal of Management. 32(3): 360–380. doi:10.1177/0149206305280789.*
44. ^a, b^ *Walkowiak E (2023). "Task-interdependencies between Generative AI and Workers". Economics Letters. 231: 111315. doi:10.1016/j.econlet.2023.111315.*
45. ^a, b, c, d^ *Yan L, Greiff S, Teuber Z, Gašević D (2024). "Promises and challenges of generative artificial intelligence for human learning". Nature Human Behaviour. 8(10): 1839–1850. doi:10.1038/s41562-024-02004-5.*
46. ^ *Eager B, Brunton R (2023). "Prompting Higher Education Towards AI-Augmented Teaching and Learning Practice." Journal of University Teaching and Learning Practice. 20(5). doi:10.53761/1.20.5.02.*
47. ^ *European Commission (2024). Living guidelines on the responsible use of generative AI in research. https://research-and-innovation.ec.europa.eu/document/download/2b6cf7e5-36ac-41cb-aab5-0d32050143dc_en?filename=ec_rtd_ai-guidelines.pdf.*
48. ^ *Kaebnick GE, Magnus DC, Kao A, Hosseini M, Resnik D, Dubljević V, Rentmeester C, Gordijn B, Cherry MJ (2023). "Editors' Statement on the Responsible Use of Generative AI Technologies in Scholarly Journal Publishing." Hastings Center Report. 53(5): 3–6. doi:10.1002/hast.1507.*
49. ^ *He J, Piorkowski D, Muller M, Brimijoin K, Houde S, Weisz J (2023). "Rebalancing Worker Initiative and AI Initiative in Future Work: Four Task Dimensions." Proceedings of the 2nd Annual Meeting of the Symposium on Human-Computer Interaction for Work. doi:10.1145/3596671.3598572.*
50. ^ *Toner-Rodgers A (2024). Artificial intelligence, scientific discovery, and product innovation. ArXiv Preprint ArXiv:2412.17866.*
51. ^ *Babina T, Fedyk A, He A, Hodson J (2024). "Artificial intelligence, firm growth, and product innovation." Journal of Financial Economics. 151: 103745. doi:10.1016/j.jfineco.2023.103745.*
52. ^ *Mason C, Chen H, Evans D (2024). "AI Adoption and Firm Demand for Workers and Skills: Insights from Online Job Postings." Qeios. doi:10.32388/LAVWIY.*
53. ^ *Einola K, Khoreva V (2023). "Best friend or broken tool? Exploring the co-existence of humans and artificial intelligence in the workplace ecosystem." Human Resource Management. 62(1): 117–135. doi:10.1002/hrm.22147.*

54. ^Liu Q, Tong Y (2022). "Employee Growth Mindset and Innovative Behavior: The Roles of Employee Strengths Use and Strengths-Based Leadership." Frontiers in Psychology. 13. doi:10.3389/fpsyg.2022.814154.
55. ^Boulus-Rødje N, Cranefield J, Doyle C, Fleron B (2024). "GenAI and me: the hidden work of building and maintaining an augmentative partnership." Personal and Ubiquitous Computing. doi:10.1007/s00779-024-01810-y.
56. ^Bernard H, Thayer JD, Streeter EA (1993). "Diligence and Academic Performance." Journal of Research on Christian Education. 2(2): 213–234. doi:10.1080/10656219309484785.
57. ^Littman-Ovadia H, Lavy S (2015). "Going the Extra Mile: Perseverance as a Key Character Strength at Work." Journal of Career Assessment. 24(2): 240–252. doi:10.1177/1069072715580322.
58. ^Masui C, Broeckmans J, Doumen S, Groenen A, Molenberghs G (2014). "Do diligent students perform better? Complex relations between student and course characteristics, study time, and academic performance in higher education." Studies in Higher Education. 39(4): 621–643. doi:10.1080/03075079.2012.721350.
59. ^Minami, T., Ohura, Y., & Baba, K. (2017). Does Student's Diligence to Study Relate to His/Her Academic Performance? In Y. Tan, H. Takagi, & Y. Shi (Eds.), Data Mining and Big Data (pp. 40–47). Springer International Publishing.
60. ^Rios JA, Ling G, Pugh R, Becker D, Bacall A (2020). "Identifying Critical 21st-Century Skills for Workplace Success: A Content Analysis of Job Advertisements." Educational Researcher. 49(2): 80–89. doi:10.3102/0013189X19890600.
61. ^van Laar E, van Deursen AJAM, van Dijk JAGM, de Haan J (2018). "21st-century digital skills instrument aimed at working professionals: Conceptual development and empirical validation". Telematics and Informatics. 35(8): 2184–2200. doi:10.1016/j.tele.2018.08.006.
62. a, bDi Battista A, Grayling S, Hasselaar E, Leopold T, Li R, Rayner M, Zahidi S (2023). The Future of Jobs Report 2023. https://www3.weforum.org/docs/WEF_Future_of_Jobs_2023.pdf.
63. ^Altrock S, Mention A-L, Aas TH (2024). "Being Human in the Digitally Enabled Workplace: Insights From the Robo-Advice Literature." IEEE Transactions on Engineering Management. 71: 7876–7891. doi:10.1109/TEM.2023.3291820.
64. ^Falkov L (2024, March 25). Upskilling and reskilling are critical to successful gen AI implementation. Ernst & Young Global Limited. https://www.ey.com/en_ca/insights/workforce/upskilling-for-successful-gen-ai.
65. ^Husic, E. (2021, March 1). Free AI education for small and medium businesses. Minister for Industry and Science. https://www.minister.industry.gov.au/ministers/husic/media-releases/free-ai-education-small-and-medium-businesses
66. ^Loh, H.-H., Beauchene, V., Lukic, V., & Shenoy, R. (2024, October 6). Five Must-Haves for Effective AI Upskilling. Boston Consulting Group. https://www.bcg.com/publications/2024/five-must-haves-for-ai-upskilling

67. ^*O'Donoghue, O., & Roberts, D. (2024). New Work, New World. https://www.cognizant.com/en_us/insights/documents/new-work-new-world-with-generative-ai-wf2064768.pdf*
68. ^*Abbas M, Jam FA, Khan TI (2024). "Is it harmful or helpful? Examining the causes and consequences of generative AI usage among university students." International Journal of Educational Technology in Higher Education. 21(1): 10. doi:10.1186/s41239-024-00444-7.*
69. ^*Bastani H, Bastani O, Sungu A, Ge H, Kabakcı Ö, Mariman R (2024). "Generative AI Can Harm Learning." The Wharton School Research Paper.*
70. ^*Lehmann, M., Cornelius, P. B., & Sting, F. J. (2024). AI Meets the Classroom: When Does ChatGPT Harm Learning? ArXiv Preprint ArXiv:2409.09047.*

Declarations

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Potential competing interests: The authors are employed by the Commonwealth Science and Industrial Research Organisation, Australia.