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Employer Expectations: The Impact of Artificial Intelligence Tools and Competencies Needed for Computing Positions

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Abstract

The rapid rise and integration of artificial intelligence (AI) are reshaping the labor market. There is an increasing expectation that workers who enter industry will pair domain-specific knowledge with AI-related competencies to thrive in their roles. Yet, it remains unclear: 1) what applications are being utilized in varying computing positions (e.g., software engineers, data scientists, AI or machine learning engineers); 2) whether upskilling or training is being offered for current employees; and 3) how job applicants may be assessed for these competencies during the hiring process. We sought to address these areas through a qualitative investigation of the perspectives of hiring decision makers, applying the framework of Social Cognitive Career Theory. We conducted semi-structured interviews with (n = 18) industry professionals involved in workforce recruitment decisions across various sectors, including healthcare, finance, logistics, technology, and consulting, and we analyzed the transcripts using reflexive thematic analysis. Our results highlighted that all employees, both current and future, will be expected to integrate AI in some capacity. Despite strong expectations for employees to possess AI skills and wanting them to integrate them into operations, only a small subset of companies reported offering in-house training or resources to learn. In addition, most employers expected baseline AI literacy, and some pointed out that certificates and coursework could indicate sufficient competence. However, some employers, who possessed high domain-specific expertise, also stressed that working knowledge and applied skills were of the utmost value. Accordingly, portfolios were considered more demonstrative of how the candidates used AI to build and deploy projects than credentials listed on a resume and were suggested as a better approach to displaying evidence of AI readiness. The findings from this investigation can serve to inform as well as offer insight on how faculty, administrators, policymakers, and other stakeholders could integrate AI-related competencies into academic preparation to meet evolving industry needs and enhance graduate employability.

1 Introduction

Artificial intelligence (AI) is transforming the nature of work in almost every sector of industry. Among these, the most profound changes are occurring in job functions that are anticipated within engineering and computing roles, as these areas are the most susceptible to transformation by AI, robotics, and automation [1, 2]. While some scholars compare the rapid acceleration of AI to paradigm-shifting revolutions such as the invention of the steam engine [3], others raise concerns that widespread AI adoption may displace workers and disrupt established labor structures [4].

Beyond possessing domain knowledge, being “AI-ready” increasingly means remaining current with fast-moving developments in tools, methods, and practices shaped by generative AI, automation systems and intelligent systems. Generative AI systems are capable of producing or predicting new content such as text, code, images, and data-driven outputs based on training on large datasets. By 2024, industry reports suggested that 75% of global knowledge workers were already using generative AI in their work, with usage nearly doubling in the preceding six months [5].

Industry conversations frequently raise the need for reskilling and upskilling [6]. Yet, it remains often unclear which forms of AI understanding are valued, if and how expectations differ across roles, and how candidates and employees are evaluated with respect to AI foundational knowledge and application. There needs to be sufficient distinction between expectations placed on job candidates entering the workforce and those placed on employees already working in computing roles. Moreover, while credentials, certificates, and coursework are often referred to as indicators of competence, less is known about their relative value for a fast-emerging field such as AI [7]. Greater insights are also needed into how employers evaluate applied skills, portfolios, and demonstrated use of AI in real-world contexts when assessing AI readiness.

Furthermore, there is a growing assumption that academic institutions will revise curricula and adjust learning environments to prepare students for emerging professional demands [8] and ensure their graduate employability. In this context, graduate employability refers not only to securing an initial job but also to the ability to apply relevant skills, stay current with digital advancements, and sustain meaningful participation in the workforce over time. Increasingly, academic institutions are held accountable for these outcomes, which can also impact their metrics and reputations [9]. Such expectations for higher education, to prepare students for an AI-driven workforce, can be especially difficult while navigating established pedagogical traditions and accreditation requirements [10, 11, 12]. Yet, failure to address these changes risks exacerbating skills mismatches and contributing to large-scale workforce disruptions [13].

These accelerating developments raise an important and urgent question: "How can academic programs evolve to prepare students and enhance their graduate employability for AI-integrated work environments?" Despite the urgency of this question, before academic institutions can make decisions on how to adequately prepare graduates, there is limited clarity about how industry hiring decision makers define and assess AI-related competencies in practice. Existing research and policy discussions have largely focused on educational strategies and institutional responses to AI integration, but less attention has been paid to how hiring decision makers evaluate AI competencies in real-world contexts, providing a critical and practice-based perspective on how workforce expectations are formed and applied.

To address these gaps in knowledge, we examined the perspectives of hiring decision makers regarding expectations for AI understanding and application among both prospective and current employees. Since different positions may have distinct job-related requirements, we focused on computing-related roles. In this study, we envision AI readiness in the context of both academia and industry. It is conceptualized as comprising (1) familiarity with AI tools and platforms, (2) applied competence in using AI within domain-specific and real-world contexts, and (3) awareness of ethical, secure, and responsible AI practices in organizational environments.

We applied Social Cognitive Career Theory (SCCT) as the basis for this inquiry. The theory highlights the interaction between individual capabilities, contextual affordances, and outcome expectations [14]. Specifically, we sought to answer the following research questions (RQs):

- **RQ1:** *What expectations do hiring decision makers have for understanding and/or application of AI for job candidates?*
- **RQ2:** *What expectations do hiring decision makers have for understanding and/or application of AI for employees working in different computing roles?*

The goal of this study is to contribute empirically informed insight into how computing and education might better align with evolving workforce expectations. This study grounds discussions of AI readiness in the lived perspectives of hiring decision makers. We conducted eighteen semi-structured interviews with industry professionals involved in hiring and workforce decisions across sectors including healthcare, finance, logistics, technology, and consulting. Using reflexive thematic analysis, we explored how AI competencies are conceptualized, differentiated by role, and shaped by organizational structure:

The remainder of this paper is organized as follows. Section 2 provides relevant background and related work that situate this study within the broader literature on AI and workforce preparation for computing roles. Section 3 describes the SCCT theoretical framework that guided this study. Section 4 outlines the research design and methods, including participant recruitment, data collection through semi-structured interviews, and the reflexive thematic analysis approach used to analyze the data. Sections 5 and 6 present the findings and discuss their implications in relation to the research questions and existing literature. Finally, Section 7 addresses the limitations of this study, and Section 8 summarizes the key conclusions.

2 Background

2.1 Situating AI withing Computing Roles

Computing education has historically evolved in response to shifts in technology, workforce demands, and applied practice [15]. Prior research highlights that computing has never been epistemologically uniform; multiple ways of knowing and practicing computing have coexisted, though not always equally valued [16]. Unlike other engineering disciplines that often require formalized access to specialized equipment, computing has long been characterized by early and informal entry points, enabling learners to acquire skills outside of institutional settings [17]. The emergence of generative AI will likely follow a similar pattern, as students start encountering AI tools prior to formal instruction in computing programs at various levels [18]. The rapid integration of AI into education and work introduces questions about competence, identity, and what constitutes "real" computing work, with some educators encouraging and others advocating restrictions on AI use in learning [19].

As AI becomes embedded in tasks such as coding, testing, analysis, documentation, and decision support, computing roles are shifting from task execution toward oversight, judgment, and system-level integration, all of which require critical thinking. These changes raise important questions about how AI should be situated within computing roles and how expectations for professional competence are evolving. To this effect, scholars have emphasized the need for closer collaboration between industry and academia to share workforce expectations and better align educational preparation with emerging demands [20, 21, 22]

Tedre, Simon, and Malmi [23] characterized computing education as cyclical, with instructional priorities shifting over time from mathematical logic and engineering toward problem-solving and computational thinking approaches in response to evolving technologies and societal needs. The emergence of generative AI represents a qualitatively different inflection point within this trajectory. More recent work argues that generative AI does not merely introduce new tools. It fundamentally alters what it means to learn, practice, and assess computing by reshaping students' relationships with code, abstraction, and problem formulation [24, 25]. Rather than focusing solely on the code-writing aspect of instruction, this paradigm shift places importance on higher-order skills of writing prompts, code evaluation, reasoning about the outputs produced, and ethical judgment. This change proposes a revolutionary shift towards a restructuring of computer science education in the context of AI-based learning.

2.2 What is known verses unknown – AI Skills and hiring

Industry reports indicate that AI is reshaping computing-intensive roles across software development, data science, information technology (IT), and related fields [2]. Employers increasingly describe AI literacy, explained as the ability to understand, evaluate, and apply AI systems, as a foundational competency rather than a niche specialization. Employers also emphasize hybrid skill sets that integrate technical expertise with communication, critical thinking, and ethical reasoning [26]. At the same time, organizations that are adopting AI in their workflows are reporting significant skill shortages and limited worker readiness [27].

Comparatively, workers report feeling underprepared to use AI effectively, even as they are expected to integrate AI into their daily workflows [5]. As AI knowledge becomes a core career sustainability skill rather than an optional specialization, employees' perceptions of their own employability and job fit are increasingly shaped by their AI readiness [28]. When such readiness is absent, whether through self-directed learning or formal education, this lack of preparedness may undermine individuals' self-efficacy and confidence in navigating AI-integrated work environments. Global reports warn that failure to develop AI-related competencies at scale could lead to significant economic disruption, with inequalities emerging not only across nations but also within organizations and teams [29]. As AI adoption accelerates unevenly, disparities in access to training and preparedness risk compounding existing workforce inequities.

More recent literature further underscores the educational implications of these trends. Gupta et al. [30] argued that generative AI is transforming how learners acquire and apply knowledge, necessitating curricular redesigns that intentionally incorporate AI-integrated learning strategies. Their work emphasized the need for coordinated action among students, educators, and policymakers to ensure that future workers are equipped to function effectively in AI-integrated environments.

Additionally, Goel et al. [31] further highlighted the importance of integrated reskilling and upskilling ecosystems that cultivate not only technical competence but also ethical reasoning and higher-order cognitive skills. Framing these concerns at a national level, Johnson et al. [32] characterized AI workforce preparation as a strategic imperative and call for educational roadmaps that better align computing programs with industry demands in a data-driven economy. Similarly, AI may reshape professional roles not only through automation but through a shift in collaboration, identity, and task structure [33]. Rastogi and Pandita [33]'s research is based on a worker's lived experiences with AI. Their findings suggest that future computing graduates need to be prepared for hybrid human–AI workflows that not only require technical judgment but also socio-technical adaptability. Complementing this interpretive view, it has been quantitatively demonstrated that AI adoption significantly affects factors such as job satisfaction, organizational behavior, and employee attitude [34]. This highlights measurable disruptions that organizations might be struggling to manage.

While this literature establishes the growing importance of AI skills, much of it relies on large-scale surveys, policy analyses, or organizational reports [34, 2, 29]. There is less clarity on how hiring decision makers interpret these expectations in practice, how AI competences are evaluated during hiring, and how expectations differ across various computing roles. Moreover, existing research maintains limited distinction between expectations placed on job candidates entering the workforce and those placed on employees already working in computing roles.

2.3 Academic Readiness for AI-Integrated Workspaces

Recent scholarship suggests that while the need for AI-related competencies is widely acknowledged, higher education is still grappling with how to define and operationalize these skills in practice. The frameworks for AI literacy increasingly emphasize not only technical knowledge but also confidence, ethical reasoning, and reflective judgment as core competencies [35]. However, educators often report uncertainty about what these competencies should look like instructionally and how they should be assessed, particularly as generative AI rapidly reshapes programming and problem-solving practices [24, 25].

Empirical evidence indicates that many instructors develop AI proficiency through self-directed learning and informal networks rather than structured institutional support, reflecting gaps in professional development and guidance [36]. At the same time, students are already adopting generative AI extensively, often in the absence of clear pedagogical frameworks or policies [37]. Collectively, this literature indicates that higher education is navigating a period of adjustment in which the importance of AI-related competencies is widely recognized. Yet, uncertainty remains regarding which skills, forms of judgment, and instructional approaches should be prioritized. Faculty must be supported with appropriate tools, knowledge, training, and instructional resources to teach emerging AI-related skills within a rapidly evolving workspace.

This study addresses this gap by examining hiring decision makers' expectations for understanding and applying AI among both job candidates and employees currently working in computing roles. Rather than treating "computing" as a unified field, this work explores the role-specific nature of AI expectations by examining how expectations vary across positions such as software engineering, data science, AI & machine learning engineer, and other roles. By grounding this investigation in the perspectives of industry decision makers who are directly involved in hiring and workforce development, this study provides empirically informed insight into how AI readiness is conceptualized in practice. In doing so, it offers contextually specific guidance for how computing education programs might better align curricula, learning experiences, and credentials with the evolving and potentially unclear demands of an AI-integrated workforce.

3 Theoretical Framework

We employed the Social Cognitive Career Theory (SCCT) as the guiding theoretical framework for this study [14], as shown in figure 1. Grounded in Bandura's theory of self-efficacy (Bandura, 1986), SCCT considers how learning experiences contribute to the development of career decision self-efficacy, outcome expectations, and ultimately performance and attainment. SCCT is a well-established model for understanding career development that explains the interconnectivity between individual factors, contextual influences, and learning experiences that shape career-related decisions and outcomes. SCCT emphasizes how environmental conditions such as organizational structures, social influences such as competitive dynamics within and across organizations, and perceived affordances or constraints shape individuals' career trajectories.

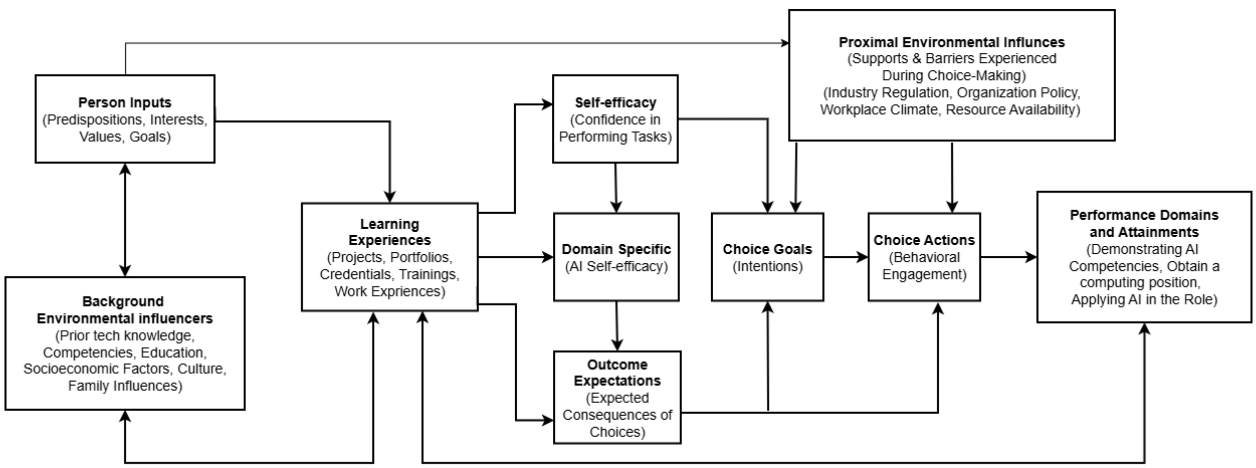

Figure 1: SCCT framework, adapted from [14]

SCCT has been used to understand pathways into computing disciplines and computing-related job roles. Lent et al. [38] described that SCCT is a robust framework for predicting interests and goals in computing, highlighting the role of both individual beliefs and environmental factors, i.e., self-efficacy, outcome expectations, and contextual support, in shaping career trajectories. Guided by SCCT, George et al. [39] investigated how college environments and institutional contexts shape students' interest in computing careers over time. They emphasized the importance of learning experiences and proximal support in sustaining participation. The study showed that strong self-efficacy, belonging, family support, and meaningful engagement in computing communities and supportive environments in classrooms are critical pillars for colleges seeking to grow the tech pipeline.

More recent studies extend the SCCT framework into examining experiential pathways into computing careers. This includes industry exposure and applied learning opportunities. For example, [40] illustrates how structured short-term industry experiences can enhance students' confidence, clarify career goals, and bridge the gap between academic preparation and professional expectations. Taken together, these studies show how SCCT can help explain the ways learning experiences, contextual factors, and self-efficacy can shape pathways into computing.

Extending this line of research, this study applies SCCT as an interpretive lens to assess how hiring decision makers' expectations for AI understanding and application shape entry into and performance within computing roles. We conceptualize AI-related learning experiences as emerging from formal education, prior work experience, and role-specific exposure to AI systems. Rather than examining individuals' self-efficacy directly, we focused on hiring decision makers' perceptions of candidate competence and readiness for AI-integrated roles. We also explored contextual influences that shape expectations for AI competence, including organizational policies, industry regulations, infrastructure readiness, and role-specific demands.

4 Methods

This study employed a qualitative research design to examine the expectations of hiring decision makers in various industries for understanding and applying AI among both prospective job candidates entering or transitioning into computing roles and current employees working in computing-related roles. Our qualitative approach was selected to capture nuanced perspectives, contextualized experiences, and role-specific expectations that are not easily observable through survey-based methods.

Institutional Review Board (IRB) ethics approval was obtained prior to the commencement of data collection. We collected feedback from industry professionals involved in hiring and workforce development decisions using semi-structured interviews. Their responses were assessed using reflexive thematic analysis [41]. Below we elaborate further on the participants, data collection, data analysis, and authors' positionality.

4.1 Participants

Participants included n = 18 industry professionals who were directly involved in hiring, supervising, or evaluating employees in computing-related roles. The participants exercised a direct influence on recruitment, evaluation, and role expectations for the current and/or future workforce. Participants were recruited through professional networks, industry contacts, and referrals. This approach was selected since we sought professionals hiring for specific roles and to ensure a mix of organizations was included. The participation of these hiring decision makers was voluntary.

Table 1 summarizes participant pseudonyms, role categories, and organizational size to provide transparency regarding the composition of the sample while maintaining confidentiality. The sample includes participants from executive leadership, technical leadership, engineering, operations, and talent-focused roles across large (n = 8), medium (n = 5), and small (n = 5) organizations. Organizational size was defined as small (fewer than 100 employees), medium (100–1,500 employees), and large (1,500+ employees).

4.2 Data Collection

The data was collected through semi-structured interviews conducted remotely using Zoom video conferencing software. Each interview lasted approximately 25-40 minutes. An interview protocol was developed to explore participants' expectations for AI understanding and application during hiring processes, as well as expectations for employees currently working in computing roles. The complete interview protocol is included in the appendix. The questionnaire included open-ended questions designed to elicit examples of the participants understanding of AI, current

Table 1: Participant Pseudonyms, Roles, and Organizational Sizes

No.	Pseudonym	Role	Company Size
1	Casey Morgan	Senior Software Engineer	Large
2	Jordan Taylor	VP, Software Architecture	Large
3	Riley Quinn	Chief Human Resource Officer	Medium
4	Alex Cameron	Director, Strategic Initiatives	Medium
5	Drew Ellis	Technical Director, AI & ML	Large
6	Taylor Reed	VP & Senior Partner	Small
7	Morgan Blake	Founder & CEO	Small
8	Jamie Cross	Staffing Specialist	Large
9	Avery Lane	Chief Executive Officer	Small
10	Rowan Clarke	Recruiter	Small
11	Shay Parker	CIO & Director, Innovation & Tech	Medium
12	Reese Donovan	Senior Manager	Medium
13	Quinn Harper	Director, Operations	Large
14	Cameron Wilde	Chief Operating Officer	Medium
15	Skyler James	Talent Portfolio Management	Large
16	Dakota Hayes	Director	Small
17	Emerson Cole	VP, Talent Acquisition	Large
18	Vera Bose	Program Manager, UX Research	Large

state of use of AI in their organizations, how AI-related competencies are assessed at their organizations, how expectations vary by role (e.g., software engineer, data scientist, AI engineer, or machine learning engineer) and organizational context, and ultimately what the expectations are from academia in preparing the next generation of AI ready workforce.

All interviews were recorded with the consent of the participants and subsequently transcribed using the built-in Microsoft Word feature to transcribe, feeding the audio file. Transcripts were manually reviewed and cleaned by the research team to ensure accuracy prior to analysis.

4.3 Data Analysis

Data were analyzed using reflexive thematic analysis, following the approach described by Braun and Clarke [42, 43, 41]. This method focuses on the identification of shared patterns of meaning across participants. In addition, reflexive thematic analysis acknowledges the interpretive role of researchers in theme development. Analysis started through familiarization with the data, initial code generation, theme development, and iterative refinement.

The authors independently reviewed the transcripts and conducted a reflexive thematic analysis following the six-phase process outlined by Braun and Clarke (2023). First, the authors started the process by getting familiarized with data through repeated, active reading of the transcripts. They made a note of initial observations and potential patterns of meaning. Second, initial codes were generated inductively, with attention to semantic and latent meanings relevant to RQ1 and RQ2. The appendix indicates which interview questions were chosen for RQ1 and which ones were chosen for RQ2. These codes captured recurring ideas related to expectations for AI understanding, application, and role-specific use. Third, the authors grouped codes into initial themes, examining how these codes represented broader patterns across interviews. Fourth, these candidate themes were reviewed and refined through iterative discussion around the collaborative interpretation. The goal was not to reach consensus but to deepen the reflexive engagement [44]. Fifth, themes were defined and named, mapping each storybook theme to the research questions and interpreting how hiring decision makers may view AI applications' value for current and future employees. Finally, the themes were integrated into a narrative and written to address the research questions. Throughout this process, the authors met multiple times to reflect on decisions, discussing codes and themes constructed.

4.4 Positionality

The first author is a senior full stack engineer and doctoral student in engineering and computing education with over fifteen years of experience working in higher education and close collaboration with industry partners. They have extensive experience designing and maintaining technical systems and have been involved in workforce-aligned initiatives related to computing and emerging technologies, including AI. The first author led the study design, conducted the interviews, co-led the data analysis, and prepared the manuscript. Their professional background at the intersection of academia and industry informed the development of the interview protocol and supported rapport with participants while also shaping their interest in understanding how hiring decision makers define and assess AI-related competencies for computing roles.

The second author is an assistant professor in computing education. Her research and teaching are centered around supporting students' technical and professional development. This includes cultivating competencies related to the adoption of AI tools with regard not only to their opportunities but also to their limitations. She has also developed and led a course around AI, ethics, and societal impact. She contributed to the study design and review of the manuscript. Her experiences and viewpoint influenced her motivation to better understand the industry perspective on what may be needed to enhance students' graduate employability.

The third author brings a perspective shaped by a strong belief in the transformative role of education in supporting professional growth and mobility. Their entry into computing followed a non-traditional pathway, with technical skills developed primarily through workplace experience rather than formal computer science training. This background informs an appreciation for the diverse ways individuals enter computing fields and the significant role of on-the-job learning. The author acknowledges that their academic and professional experiences have been largely free of significant learning barriers, which may limit firsthand insight into the challenges faced by adults encountering structural or institutional obstacles in computing careers. While a belief in human adaptability and growth motivates a focus on opportunity and skill development, the author remains attentive to how this perspective may shape the framing and interpretation of findings and strives to critically reflect on assumptions embedded within the research process.

5 Results

Below we present the results of the thematic analysis in relation to each RQ.

5.1 RQ1: What expectations do hiring decision makers have for understanding and/or application of AI for job candidates?

Based on the responses to questions for RQ1, we constructed four themes. These themes captured how the hiring decision makers described how they evaluated AI competencies during hiring and what other skills they gave priority alongside AI. Across these interviews, the participants emphasized applied competencies, human judgment, and having a baseline of AI knowledge as central consideration when hiring new employees.

Theme 1: Skills Over Credentials in AI Hiring

Hiring decision makers consistently emphasized that they preferred that the candidate demonstrate applied AI skills rather than just show formal credentials (e.g., degrees, certifications). Applied skills were equated with a candidate being more "AI ready." This emphasis might be a general broader shift towards skill-based hiring in general. In the case of AI as a skill, the candidate was expected to show how they had engaged with tools in a pragmatic and meaningful way.

Portfolios were described as a central mechanism for assessing AI competence. This allowed the job candidates to make their learning visible. As one hiring manager explained, *"Show me the portfolio. What have you done? And carry me through what [you] have been exposed to in terms of AI and what [you] have been exploring."* Portfolios provided proof of exposure to AI tools and evidence of candidates' ability to apply AI in real-world contexts relevant to the role. In line with this perspective, hiring decisions were framed around demonstrated skills and problem-solving ability rather than what was shared on a resume alone. As Jordan Taylor stated, *"When it comes to understanding and assessing their AI knowledge, we do expect them to show what projects they have worked on."* Coursework in college, certificates, or computer science or related degrees were described as helpful, but they did not indicate the AI readiness of the candidate. As Vera Bose explained, *"Right now, coursework and so forth is not something that's looked at as a requirement."* Instead, hiring decision makers placed greater value on candidates' ability to demonstrate how they have used AI tools to solve problems or support workflows.

During the hiring process, job candidates may also be requested to support claims made on their resume by displaying their technical prowess through tasks completed. Automated systems could also be used to determine how well this was accomplished. As exemplified by Skyler James' comment:

> *A lot of our assessment providers have really matured, where it's going to pick up the hard skills. Let's say prompt engineering, data engineering, and Python were scanned on your resume—you will now be given simulations where you'll actually have to apply that skill to a task, and then the hiring managers will be able to see how you performed against that. In some cases, the system will recommend a proficiency for how well you applied that.*

Also, employers spoke to how the kinds of competencies, including specific tools or programming languages, may have evolved in light of AI. For example, Shay Parker shared:

> *For software engineers, I recently started asking for Python, which was not required five years ago; now it is mandatory, and I require all software engineers and business*

> *analysts developing applications to have at least an entry level of Python. Of course, I still ask for Visual Studio, .NET, C#, C++, or basic languages, HTML, Java, and JavaScript, but Python is something we added in the last years.*

An important exception to skills-based hiring was noted for highly specialized or research-intensive roles. Positions requiring deep technical or research expertise continued to prioritize advanced formal credentials, such as doctoral degrees. In contrast, for more applied or implementation-focused roles, alternative credentials were viewed equally viable. This distinction is illustrated by one participant, Taylor Reed, who stated:

> *The employers who are looking for very experienced people are looking for PhDs in computer science with specializations in things like computer vision and machine learning. Then we have other roles—for example, front-end engineer–type roles—where I'm seeing that boot camp certifications and certification programs from universities work just as well as the higher education degree programs.*

Theme 2: Baseline AI Literacy as an Entry Point Expectation, Academia as Primary Source

Candidates' familiarity with commonly available AI systems was treated as a bare minimum expectation rather than an advanced or specialized skill. Formal credentials were not deemed essential by some participants. However, many of them still placed a high value on academic institutions to teach students the AI literacy that was expected.

Several participants explicitly referred to popular generative AI tools as part of this assumed baseline knowledge. As Drew Ellis noted, *"We expect that people at least know how to use any publicly available chat-enabled large language models, ChatGPT or Claude."* The participants kept coming back to the applied aspect of the knowledge and defined it as a baseline expectation as well. As Riley Quinn explained, *"What have you learned, and from what you've learned, what have you applied practically? [...] Not only foundational knowledge but [also] applied knowledge around AI are indeed foundational responsibilities of every role in the company."* Some hiring decision makers took this further and added that having domain-specific knowledge would also be a great advantage. As one of the participants, Jordan Taylor said:

> *They should also have an understanding of how they can create new prompts that produce different outputs based on certain use cases. Maybe they can explain for a particular domain, because we deal with financial domains, if they have done something that helps the financial domain.*

Participants also spoke to how such shifts may manifest during the hiring process. As Vera Bose mentioned:

> *Within the past year that an aggressive shift has been taking place and really leaning into the candidate demonstrating the understanding of not only generative AI is like a tool that we all sometimes use in our personal life, but also how it can be used in the workplace. And so now we actually have interview questions that focus on generative AI use, which wasn't there before. A year ago, we never used to actually ask pointed questions about that.*

Likewise, Rowan Clarke shared:

> *For example, there was a company we were working with recently, and they expected their researchers during the take-home task to actually use AI tools. Because you get a set time limit—I think it was two hours—so they're quite respectful of the candidate's time, and there's not really loads you can do in two hours. However, if you use AI tools in order to get more done, that's more of a good signal to companies nowadays. Whereas before, it was a little bit of a sensitive subject: 'Should I use AI tools or not? Or should I show my raw knowledge?' So I think it's becoming more widely accepted that you should know how to leverage different tools to make you more productive, even if it's not directly related to what you're building or whatever.*

When referring to academia, the participants expressed wide-ranging views on the role of colleges and universities in preparing candidates to be AI-ready. Some participants indicated a gap between academic preparation and current industry expectations for AI skills. They emphasized that this gap is partly driven by the rapid pace of technological change and the limitations of academic infrastructure. As Dakota Hayes explained, *"Because it's moving so quickly, and because there are tools that employers might be using that academic institutions are not even aware of yet, it's really hard."* Participants also highlighted the importance of providing students with access to relevant AI tools, resources, and learning environments. Cameron Wilde asserted that:

> *How much exposure [to tools and resources] they can give their students and their community. That will help them to analyze these models, to understand how it works, and what can be done. If you're not ready for it, then I think you're setting your students up for failure because they would not have that exposure when they go out in the world and say, 'Oh, this can be done. I didn't know this.'*

As a response to these challenges, participants emphasized the need for closer collaboration between academia and industry. Such partnerships were viewed as essential for aligning curricula with rapidly evolving AI-related workforce demands. As Taylor Reed stated, "*I think the only way students become successful in this new world is when employers and educational institutions are really working hand in hand in transformational partnerships.*"

These expectations on academic institutions made them central actors in shaping baseline AI readiness for computing graduates. The broader implications of this finding on curriculum design, instructional practices, and graduate employability in general are further explored in the Discussion section.

Theme 3: Human Judgment in AI-Augmented Work

Hiring decision makers consistently described AI as a tool to augment, rather than replace, human work. Such framing is noteworthy given that in academic environments student are anxious about AI-related job displacement is common [45]. This contrast highlights a disconnect between student perceptions and industry expectations, indicating an opportunity for educators to create learning environments where AI could be reframed as a collaborative tool.

Participants reported that AI reduces routine "grunt work," allowing employees to focus on higher-order cognitive tasks. As Taylor Reed explained, "*My hope is that these tools are* *leveraged to help us accelerate as people, so we no longer have to do the 'grunt work' that takes up a whole lot of time and energy and doesn't necessarily allow us to use higher-order thinking.*" Similarly, taking on efficiency gains, Avery Lane noted that AI was expected to replace tasks rather than people, stating, "*I think it's going to be transformational, yes. I don't think it is necessarily going to replace people, but it will definitely replace many of the tasks that people do today.*"

AI was frequently described as useful for assisting with documentation, summarization, and analytical tasks. Participants noted that using AI in these areas allowed employees to reallocate effort toward more complex and strategic work. Emerson Cole emphasized this point, stating, "*Using generative AI for documentation and for proof of concepts is going to be very, very critical going forward.*" Participants also framed AI as "augmented intelligence," a term that reinforces the continued importance of human expertise. This framing serves not only to clarify organizational expectations but also to support employee confidence by positioning AI as a complement to, rather than a replacement for human judgment. As Riley Quinn explained, "*The way we internally refer to AI is not 'Artificial Intelligence,' but rather 'Augmented Intelligence.'*"

Alongside AI use, hiring decision makers strongly emphasized the importance of non-technical skills, including communication, problem-solving, and critical thinking skills. As exemplified by Dakota Hayes:

> *Non-technical skills are communication, critical thinking, what I would consider to fall under project management skills—the good follow-up, being able to communicate by e-mail, public speaking, ability to do conflict resolution, whether it's internally within a team or externally with client-facing or key stakeholders. I think those are some of the crucial things that employers are looking for when hiring.*

Similarly, hiring decision makers stressed that critical thinking should remain a priority independent of AI tool use, emphasizing judgment, reasoning, and thoughtful decision-making over technical tool mastery alone. This perspective was reinforced by this perspective, stating, "*I think it's beyond AI; I think it's about making sure that we're still prioritizing critical thinking.*" Likewise, Sklyer James shared:

> *We've seen an increase in prompt engineering on NLP, a lot around data engineering and data governance. And then we are starting to see even some of the softer skills be more emphasized—things around adaptability, critical thinking, problem-solving, communication agility, even things like growth mindset are making it onto some of the technical roles as well.*

Theme 4: Surface-Level Ethical Expectations

Ethical considerations related to AI use were consistently mentioned by hiring decision makers, though expectations were often framed at a surface or compliance-oriented level. Participants described ethical awareness as important, but such discussions frequently focused on adherence to policies, regulations, or certifications. There was less emphasis on deeper ethical reasoning or critical engagement with AI's broader implications. Some participants framed ethical competence in terms of avoiding harm or ensuring alignment with organizational values. As Morgan Blake stated, "*If the implementations [of AI] happen to be unethical, then know-how goes contrary to societal value.*" However, the ethical considerations themselves were often discussed in abstract terms. Some participants suggested that a basic understanding of fairness and bias, without expressing any advanced expertise, was sufficient. As Drew Ellis expressed, "*As long as they know some standard framework and why fairness- and bias-aware models are important, that should be enough.*" No participant articulated how ethical reasoning would be evaluated during hiring. Participants also referenced certifications or formal training as indicators of ethical competence in AI use. One hiring manager Dakota Hayes suggested that businesses might look for credentials, stating, "*I would say businesses would need to look for AI ethics and AI governance as leading certifications when it comes to generative AI.*"

Compliance-oriented framing, focused on safeguards and individual accountability rather than deeper ethical deliberation, was further illustrated by Reese Donovan, who emphasized that:

> *The company that I work for currently stresses that at all points in time. We do have an AI Council. If there are any questions, you have a point of reference in terms of understanding ethical things. Of course, the main commandment is that you are 100% responsible for whatever output you get. Rather than just understanding that that's an output from any AI, you have to understand that you are now the owner of that output, fully responsible for it. You have to check it before you put it in front of anybody. Also, part of the extra licensing in the company (for example, Copilot) is to make sure that things are staying in a safe environment, they stay protected, and that no data is being placed anywhere. From my team, I do ask that whatever they're doing through other methods or other AI tools that are not the ones that the company fully is willing to stand behind or the licenses that protect us, that they are very, very careful as to what information they're integrating into their prompts.*

5.2 RQ2: What expectations do hiring decision makers have for understanding and/or application of AI for employees working in different computing roles?

We constructed four themes that characterized how hiring decision makers evaluated AI competencies among the current workforce and what expectations they held regarding employees' application of AI in their roles. These themes illustrated that AI integration in computing roles is shaped by role-specific expectations, competitive pressures, organizational infrastructure, and varied approaches to upskilling. While organizations are actively experimenting with AI, integration remains uneven and contingent on context. Across all themes, participants emphasized that responsible use, verification, and human judgment remain central to professional practice, even as AI becomes increasingly embedded in workplace workflows.

Theme 1: AI Integration Is Uneven and Strongly Role-Dependent

Participants consistently described AI integration as "uneven" within organizations. The expectations around its integration varied substantially by role, department, and their business functions. Instead of a standardized organizational mandate, AI use was framed as contingent on relevance to specific workflows and responsibilities. As Quinn Harper reflected, "*From what I've seen so far, AI should be used or should be leveraged, differently and smartly, in order to add value to your job.*"

Hiring decision makers also emphasized that expectations differed sharply across roles, even within the same organization. As Reese Donovan noted, "*Aside from that and the rest of the company, it really just depends by the role.*" Jordan Taylor described this distinction by stating, "*All departments don't have the need to know AI and be proficient in AI. There are some departments that do require skills, but in my department we don't. It's a nice to have them.*"

The roles in which AI competences were more clearly expected included product management, engineering, and data-oriented roles. One participant suggested that AI expectations were already embedded in these roles, noting that "*I would venture to say that anybody within the Product and Engineering organization is expected to have some of this.*" Similarly, another participant highlighted the growing relevance of AI beyond traditional technical roles, stating that, "*AI for project managers is an area where it would certainly be more useful and advantageous to have that knowledge.*"

Moving beyond formal role definitions, expectations for AI-related competencies were also shaped by employees' career aspirations. Organizations offered upskilling opportunities and expected employees to take initiative in pursuing learning aligned with their professional interests. Echoing this sentiment, Skyler James explained, "*Yes, there's a ton [of learning opportunities]. And it pretty much comes down to the role base and also, from an aspiration perspective, where you want to go. We have an internal marketplace that understands those elements and then recommends the upskilling pathways.*"

Theme 2: Competitive Pressure Drives Experimental AI Integration

AI integration was frequently framed as a strategic response to competitive pressure rather than solely a technological initiative. Organizations are adopting AI to avoid falling behind peers or competitors. They also often begin with experimental pilots and prototypes rather than large-scale deployment.

One hiring manager articulated this competitive logic directly, explaining that organizations feel pressure to continually upgrade their tools and systems because "*If they do not update and upgrade themselves or transform their application, somebody else is going to come and beat them.*" Other participants reinforced this sentiment by describing how internal benchmarking practices were used to motivate AI adoption across teams. For example, one hiring manager detailed the deliberate use of dashboards to compare departments' AI engagement, noting:

> *We can do that by implementing some things such as leveraging FOMO [Fear of Missing Out] and having dashboards showing which departments have the most and best use cases for AI. Trust me, those managers want to see their name on that board. And if they see, 'No, we have zero use cases, we don't have individuals using AI,' they want to encourage that, and they want to see their names on that board.*

While still being driven by competitiveness, AI integration for organizations often began through selective pilots rather than immediate large-scale implementation. As Cameron Wilde explained, "*We are testing certain software applications that help our business, the current applications or tools that we use—again, they don't want to be left out—are upgrading themselves.*" Drew Ellis similarly emphasized the use of AI for rapid prototyping and explained:

> *Data scientist roles, at least in my team, can be utilized in a couple of ways. One is to*

> *help write or create products—or at least very fast creation of an MVP [Minimum Viable Product] or prototype—using, let's say, a code helper.*

Theme 3: Organizational Capacity Shapes AI Upskilling and Integration

Participants consistently described organizational capacity as a central factor influencing both the pace of AI integration and the structure of AI upskilling initiatives for employees. Whereas Theme 1 highlighted that AI adoption was highly role-dependent, the theme of "Organizational Capacity Shapes AI Upskilling and Integration" emphasizes that integration was also uneven across organizations and shaped by broader structural factors such as company size, access to resources, and the availability of external support.

Differences in organizational capacity appeared to shape how strictly AI competencies were defined and evaluated. Larger organizations were described as holding more stringent expectations for workforce competencies, often due to greater access to resources and capacity to focus on specialized projects. One participant (Reese Donovan) explained:

> *I think that we're not as sophisticated in the requirements that we're asking for. I think that other companies that are maybe bigger, that have more resources to focus on specific projects, would become very strict with the courses they request and how they evaluate.*

Participants also described mandatory training being implemented as part of organizational policy. As Casey Morgan noted:

> *We are having rigorous training sessions that we are all mandatorily required to complete. These sessions range from AI courses to making sure we are aware of the different forms of generative AI and knowing how to use them, including prompt engineering.*

In organizations that are constrained by resources, participants described reliance on external or community-based programs to support AI exposure and training. Taylor Reed, for example, highlighted, "*Some of the small businesses we support are using [Community College]'s new AI for Small Business or AI for CEOs [...] Some companies are using and leveraging those free community resources as well.*" Organizations also commonly turned to third-party platforms such as Coursera or Udemy to support employee upskilling. One participant Taylor Reed noted, "*I don't know that anyone is providing easily accessible, low-cost opportunities for people to upskill where it's clear there's a place they can go to get very good upskilling—outside of a Coursera-type platform.*" In some cases, vendor partnerships also shaped both which AI tools were adopted and what training opportunities were offered. As Emerson Cole explained, "*We have training for all of our engineers that they completed. We built it and partnered with Microsoft to create a custom training program for all of our engineers on how to use Copilot.*"

Theme 4: Human Verification and Responsibility Remain Central to AI Use

Participants acknowledged the increasing integration of AI while consistently emphasizing the continued need for human oversight, verification, and responsible judgment. For instance, Alex Cameron commented "*I think what's most important for leveraging AI is recognizing that there's* *still a human aspect of it that it's not just copy paste.*" They cautioned against treating AI as authoritative and stressed that outputs must be checked especially in decision-critical contexts.

As Jaime Cross, noted, "*If [AI is] used properly and the answers are verified, [it] can improve the work in the workforce.*" Likewise, Taylor Reed echoed a similar sentiment, emphasizing that while it is important to be skilled in using AI tools, such use must be applied with regard for ethics. This perspective was reinforced by the statement, "*So yes, they need to be skilled in using these types of tools, but they also need to use them responsibly.*"

This emphasis on verification extended beyond correctness and delved into areas of maintenance, security, and even system performance. As one participant (Emerson Cole) highlighted:

> *Everybody loves new development; that's normal. Who doesn't love to create something from scratch? But a lot of code actually just needs to be updated, maintained, developed, and made more secure. Leveraging tools to be able to do that, manage data processing, make things more efficient, and continue to enhance concepts—whether it's user experience, latency, or other areas—is critical. They may understand how to create code with AI and apply quality assurance, but I think they're missing some aspects around: How do I make it way more secure? How do I get the calls to go back to the data sources in a better, more secure way—or faster way—with reduced latency?*

6 Discussion

The results of this investigation are multifaceted. We go into further detail about the findings in relation to each of our RQs in this section.

6.1 RQ1: What expectations do hiring decision makers have for understanding and/or application of AI for job candidates?

Hiring decision makers in this study consistently highlighted wanting to see applied AI competence over formal credentials. They described portfolios, projects, and demonstrations of AI use as more meaningful indicators of readiness. This reduces dependency on coursework or certificates alone. This finding from hiring decision makers reinforces some prior industry-oriented research, which suggests that employers are increasingly prioritizing skills-based hiring and observable competence over traditional signals such as degrees or certifications [26, 27]. From the perspective of SCCT, these expectations indicate the importance of learning experiences that directly shape potential job applicants' outcome expectations. Satisfying these expectations also increases an employee's self-efficacy beliefs about their employability and job fitness. If a candidate can demonstrate the use of applied AI to hiring decision makers with verifiable evidence, that indicates that prior learning experiences have translated into workplace-relevant competence.

The hiring decision makers generally assumed that new candidates entering the profession would possess a basic level of AI literacy. They also expected them to be particularly familiar with generative AI tools. This assumption reflects broader workforce research that positions AI literacy as one of the core competencies rather than a specialized skill [2, 5]. The hiring decision makers expected colleges and universities to be responsible for teaching this foundational knowledge to the next generation of the workforce. However, there was also an acknowledgment that universities might be struggling to keep up with the pace at which AI skills and integration were advancing. These findings reinforce a disconnect between what employers expect graduates to know and the limitations of higher education [30, 32].

Domain-specific knowledge was also something that was considered to be of value, besides just general AI competencies. This does not come as a surprise, as prior research has suggested that technology use in professional settings to be effective depends on the ability to apply the knowledge in specific situations and having a contextual understanding [33]. Within SCCT, this finding reflects how domain-relevant learning experiences can contribute to stronger self-efficacy beliefs. This is because individuals are better able to connect the AI skills they acquire with meaningful performance outcomes in workplace settings.

Hiring decision makers were clear to indicate that AI tools were seen as something that would augment human work. These tools were not expected to replace human judgment. Skills such as critical thinking, communication, and problem-solving were seen as essential competencies alongside AI use. These insights align with prior scholarship arguing that AI integration shifts the nature of computing work toward oversight, interpretation, adaptability, and decision-making rather than task execution alone [46, 47]. From an SCCT lens, this suggests that performance in AI-integrated roles, besides technical skills, also depends on professional dispositions that support confidence and the environments and culture that an organization supports.

Turning to moral considerations, participants consistently raised ethics as an expectation for AI use. However, these discussions were most often framed in terms of compliance with organizational policies, or ethics certifications, or even governance frameworks. While it is reasonable for industry AI practices to emphasize adherence to guidelines and risk management, this perspective contrasts with academic scholarship, which conceptualizes AI ethics as deeper engagement with issues of bias, power, risk, and broader societal impact [10, 11]. Ethical competence should not be limited to following rules but should involve critical examination of how AI systems shape decision-making, reinforce inequities, and can initiate long-term consequences. If we interpret the finding through this lens, there is a divergence between how ethical readiness is understood in industry versus academia. Hiring decision makers' expectations appeared oriented toward ensuring compliance and minimizing organizational risk, academic treatments of AI ethics foreground reasoning, systemic bias, and social responsibility. The first author's background in AI ethics coursework makes this contrast particularly visible. The analysis suggests that ethical reasoning emphasized in educational contexts may not yet be fully reflected in workplace expectations. This provides an opportunity for educators to think about how ethical reasoning should be taught, so it is translated into professional practice. Universities should emphasize the need to adequately prepare graduates to identify and rectify ethical risk and challenges in increasingly AI-integrated work environments.

6.2 RQ2: What expectations do hiring decision makers have for understanding and/or application of AI for employees working in different computing roles??

Expectations for AI use among employees were uneven and strongly role-dependent, varying across departments, business functions, and career trajectories. Rather than reflecting uniform organizational mandates, AI expectations were contingent on the perceived relevance of AI to specific workflows. This finding aligns with prior research suggesting that the impacts of AI are mediated by organizational context, influencing roles, attitudes, and workplace practices in uneven ways rather than producing uniform effects across the workforce [34]. Product management, engineering, and data-oriented roles were most frequently identified as requiring AI competence, while many other roles positioned AI skills as optional or merely a “nice to have.”

Specific technical competencies requested have also begun to shift with these evolutions in AI, such as software engineers being expected to know Python programming languages. Python is increasingly considered synonymous with AI development due to its simplicity and extensive packages, libraries, and frameworks (e.g., Pandas, TensorFlow) [48, 49]. For instance, Meta (formerly Facebook) released PyTorch, an open-source software (OSS) machine learning library commonly used for deep learning tasks [50]. Its ability to create and run computational graphs has valuable implications for model creation and debugging [51].

Hiring decision makers also described higher expectations for AI engagement among employees seeking promotion or transition into AI-adjacent roles, indicating that AI-readiness is dynamically linked to career trajectories and advancement pathways. These patterns reflect the ways in which contextual influences within organizations shape employees’ perceptions of the value of AI-related skills and inform their career-related decisions, aligning with the roles of outcome expectations and choice actions as informed by SCCT.

It did not come as a great surprise that competitive pressure further motivated AI integration, with participants describing concern about falling behind peers or competitors as a key driver. This aligns with research showing that competitive organizational climates influence employee AI acceptance and use over time [52]. Within SCCT, these competitive pressures function as a contextual influence and a factor that influences individual skill development and career development.

The participants indicated that the integration of AI into workflows was introduced through pilot programs, MVP development, and experimental use before broader integration. This practice aligns with organizational research showing that phased AI implementation, starting with pilots, serves as a mechanism for managing uncertainty, addressing resource constraints, and mitigating risk. This is particularly advantageous when integrating complex or unfamiliar technologies [53, 54].

Organizational infrastructure and access to resources heavily influenced the ability to scale AI integration. Larger organizations were perceived as having greater capacity to define strict competency requirements and implement structured upskilling initiatives, while smaller organizations relied more heavily on external platforms and community resources. [29] highlighted such structural inequities in access to reskilling opportunities and technological infrastructure. These constraints on access to training and tools hinder learning opportunities and employees’ self-efficacy related to AI use.

Finally, the hiring decision makers emphasized the need for human verification and responsible use of AI. This was particularly important in decision-critical environments. This perspective aligns with existing literature that conceptualizes AI as a socio-technical system designed to support human goals, requiring ongoing human oversight rather than autonomous decision-making [31]. Viewed through SCCT, these expectations emphasize how learning experiences contribute to employees' beliefs about their capability to use AI responsibly, linking ethical judgment and accountability to self-efficacy in AI-integrated work rather than to technical proficiency alone.

6.3 Implications and Recommendations

Implications for Curriculum Design and Experiential Learning

Academic institutions should encourage their computing programs to place greater emphasis on applied, portfolio-based learning experiences. These experiences enable students to demonstrate AI use in authentic and domain-specific contexts. Given industry expectations for baseline AI literacy and applied competence, relying on coursework or credentials alone may be insufficient for preparing graduates for AI-integrated roles. Academic institutions should work more closely with industry to provide students with opportunities to engage in real-world projects, which may also be integrated into capstone experiences. Students should also be given opportunities to experiment with AI tools as part of their coursework.

Findings from this study also suggest a potential gap between the emphasis on reflective ethical reasoning in academic settings and the more application-driven expectations observed in hiring contexts. The employers emphasized responsible AI use, but their evaluation of candidates was more closely tied to demonstrated ability to apply AI tools in practical workflows. Academic institutions should more intentionally integrate ethical reasoning into applied, project-based curricula. This will ensure that students develop both critical awareness and the ability to operationalize responsible AI practices in real-world contexts. Taken together, these efforts may help bridge the gap between academic preparation and workplace expectations.

Implications for Student Skill Development and Agency.

Academic institutions need to look beyond mere technical exposure. Curricula should provide structured opportunities for students to articulate their decision-making processes when using AI tools. Such experiences can support the development of critical thinking, responsible AI use, and confidence in applying AI effectively. These efforts may better position graduates to navigate environments where AI is increasingly integrated into everyday workflows.

Implications for Industry Training and Workforce Development.

From an industry perspective, additional upskilling of employees is increasingly important. Hiring stakeholders expressed clear expectations for applied AI competence; however, several organizations reported limited formal structures for AI upskilling once employees are hired. This places greater responsibility on organizations to invest in ongoing learning opportunities that support role-specific AI use, ethical judgment, and human oversight. To help employees translate baseline AI literacy into effective workplace practice, organizations should implement structured onboarding, internal learning pathways, and clear guidance around responsible AI use.

Implications for Industry Training and Workforce Development.

The findings highlight a misalignment between employer expectations and available training structures across both academic and workplace settings. Students need to be prepared with current, ethically grounded AI skills that align with evolving workforce needs. Without such alignment, expectations for AI integration may outpace both graduate readiness and organizational capacity.

7 Limitations and Future Directions

In this investigation, we conducted semi-structured interviews with a sample of hiring decision makers. Consistent with reflexive thematic analysis, the goal of this study was not to achieve statistical saturation [43] but to explore patterns of meaning in the experiences of hiring decision makers. As such, the viewpoints collected are not necessarily representative of the comprehensive variety of organizational scenarios, sectors, or geographies. Expectations concerning AI skills might also have been influenced by factors like the size, sector, regulatory framework, and level of AI integration, which might differ significantly from the firms chosen for this investigation. Expanding the participant pool to include a broader range of industries, international contexts, and organizational structures could yield additional insight into how AI expectations are formed and enacted across different settings.

Another drawback has to do with the fixation on the views of hiring decision makers. Although it is true that the hiring decision makers are essential to the construction and definition of the criteria and expectations related to job performance, it may also be true that their views are not comprehensive with respect to the actual experience of AI on the employees' level. Future research may triangulate the information shared with the inclusion of input from entry-level professionals with related experience relative to more senior AI or computing professionals and students entering the field.

Lastly, given that this research adopted a qualitative methodology focused on reflexive thematic analysis, this data can be considered interpretive. Even though this research focused on incorporating an element of reflexivity, the themes identified should be understood as contextually situated and informed by positionalities of the authors rather than exhaustive. Future research could consider complementing this information by utilizing a methodology that combines different approaches, long-term studies, or comparison research studies.

8 Conclusion

This paper examined hiring decision makers' expectations for AI understanding and application among both job candidates entering computing roles and employees currently working in those roles. Grounded in SCCT, the findings highlight how expectations for AI readiness are shaped by learning experiences, contextual influences, and evolving interpretations of professional competence. Across both research questions, hiring decision makers stressed practice over formal qualifications, considered familiarity with AI to be an expectation for entrants, and saw AI as an instrument designed to support, not substitute for, human judgment.

On the other hand, the research highlights some tensions. There was a broad variation in the requirements concerning the competence of AI; ethical considerations were often framed at a surface or compliance-oriented level. Responsibility for preparing AI-ready graduates was frequently placed on academic institutions, despite the recognized constraints these institutions face, such as limited infrastructure and the difficulty of keeping pace with rapid technological change. The above points to the fact that the idea of being AI-ready is a dynamic and not a static concept. These findings suggest that AI readiness is not a static concept but a dynamic one, shaped by organizational needs, competitive pressures, and uneven access to resources and training.

Taken together, this work points to the need for a tighter alignment between education in computing and the lived realities of an AI-integrated workforce. While higher education is not intended to function as vocational training alone, the results suggest avenues for more deliberate incorporation of applied AI experiences, ethical reasoning, and professional judgment into the curricula in computing. A nuanced understanding of how AI competence is framed and evaluated in practice will help educators, institutions, and industry partners work together in support of graduate employability and prepare students for sustained participation in rapidly evolving computing careers.

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Appendix

Interview Protocol for Hiring Decision Makers

Theoretical Alignment

This questionnaire was developed following the Social Cognitive Career Theory (SCCT) framework, specifically:

- **Self-Efficacy:** While self-efficacy in SCCT refers to individuals' beliefs in their own capabilities, the present study focuses on hiring decision makers' perceptions of candidate competence and readiness for AI-integrated roles. These perceptions may influence hiring decisions and shape the opportunities available to job candidates.
- **Outcome Expectations:** How do hiring decision makers perceive the impact of AI skills on job performance, productivity, and organizational outcomes.
- **Environmental Influences:** How do organizational expectations, industry trends, leadership decisions, and levels of AI adoption shape hiring practices and influence graduates' learning and career trajectories?

Interview Questions

Section 1: Introduction

(RQ1)

1. Please describe your organization.
   - What is their primary sector or purpose?
   - How large is the company?
   - Where do they operate?
2. Please describe your current role in the organization.
   - What is your title?
   - How long have you been in your current role?
3. What types of computing roles does your organization typically hire for? (e.g., software developers, data scientists, cybersecurity specialists, IT administrators)
   - What about software engineers?
   - What about data scientists?

Section 2: Hiring Trends

(RQ1)

1. Have you noticed any shifts in the types of skills and qualifications you prioritize in hiring over the last few years?
2. What outcome expectations do you have for job candidates in their understanding and/or application of AI?
3. Are AI-related skills something you currently require in new hires, or are they considered a nice-to-have for future needs?
4. Does your organization require or prefer AI-related certifications or coursework from job candidates?
5. How do you evaluate a candidate's AI knowledge or proficiency during the hiring process? (e.g., technical assessments, portfolio reviews, interviews)

6. Please describe any specific AI-related skills or competencies that you find recent graduates may lack when they enter the workforce?
7. Please describe any specific AI tools or platforms (e.g., ChatGPT, TensorFlow, AutoML) that you expect candidates to be familiar with, if any.
8. How do you envision educators could better prepare students to develop competencies or skills relevant for AI use or understanding?
9. *Introduce GenAI* What expectations do you have for job candidates in their understanding and/or application of generative AI?
10. How important is an understanding of AI ethics and responsible AI development in hiring decisions for recent graduates?
11. How do you envision educators could better prepare students to develop competencies or skills relevant for generative AI use or understanding?
    - Ethical considerations?
    - Learning new tools?
    - Prompt engineering?

Section 3: Current Employees

(RQ2)

1. Does your organization have a strong focus on AI integration in its operations? If so, how?
2. How do you see AI impacting job responsibilities in computing roles over the next decade?
3. Please describe any AI-related training or upskilling programs your organization may provide for your employees.
4. Are there particular computing roles where AI skills are more critical than others? If so, which ones and why?
5. *Role Specific Applications* How do you envision generative AI may be applied or used in the following roles at your company?
    - Software engineering roles?
    - Data scientist roles?
    - AI engineer roles?
    - Machine learning engineer roles?

Section 4: Closing

(RQ1,RQ2)

1. Is there anything else you think is important to know about AI hiring trends or skills expectations in computing?