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Ai Literacy as A Career Competency: Towards A New Dimension of Employability

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Abstract - Today, most employability frameworks used by career development cells and campus placement offices were written before generative AI existed, as shown. A typical checklist still asks whether a graduating student can use spreadsheet software, format a professional email, or speak confidently in an interview. These competencies matter, but they quietly assume a labour market in which the main risk is a skills gap rather than a moving target. This paper argues that AI literacy deserves to be considered as its own dimension of employability, not folded into the existing catch-all "digital literacy" or dismissed as a vague, of-the-moment buzzword. Synthesizing, various frameworks like human capital and automation research, established employability frameworks, Career Construction Theory's adaptability resources, the digital-literacy tradition, technology-adoption models, and the emerging AI-literacy competency literature, we propose to develop a four-part conceptual structure operational, critical, ethical, and adaptive AI literacy and argue that only the last of these genuinely distinguishes this competency from ordinary technology skill-building. The argument matters most for career-development cells and campus recruiters, who currently have little shared vocabulary for distinguishing a student who merely uses AI tools from one who uses them with genuine judgment. We close with a proposed measurement agenda and a set of practical implications for career-services cells and employers, while being candid about where the construct risks collapsing into exactly the kind of empty buzzword it is meant to replace.

Index Terms - AI literacy, Employability, Career adaptability, Digital literacy, Generative AI

AI LITERACY AS A CAREER COMPETENCY: TOWARD A NEW DIMENSION OF EMPLOYABILITY

Ask a career-services officer at most business schools what they mean by employability, and you will usually get to hear a version of the list: communication skills, teamwork, analytical ability, and, somewhere near the bottom, "computer proficiency" or "digital skills." That list has been remarkably stable for the better part of two decades, which is itself a little strange given how much the underlying labour market has changed. It has also, until quite recently, been a reasonably defensible list. Digital literacy in the 2000s and 2010s meant something you were fairly bounded or knowing your way around office software, being comfortable online, perhaps some basic data literacy. It was a skill you could acquire once and expect to hold onto.

Generative AI does not sit comfortably inside that older category and treating it as though it does as one more line item under "digital skills," taught in a single onboarding module and then assumed complete, misses something important, about how the technology behaves.

AI tools are changing monthly, sometimes weekly. Knowing how to use a specific model well this year offers only a loose guarantee of knowing how to use whatever replaces it next year, and the pace at which generative tools are already reshaping entry-level task composition

(Eloundou et al., 2023; Brynjolfsson et al., 2023; Noy & Zhang, 2023) suggests that this is not a temporary adjustment period but a standing feature of the labour market. Graduates are now entering, using these tools well involves a kind of ongoing judgment when to trust an output, when to push back on it, when not to use the tool at all, that has no real analogue in learning to use a spreadsheet. This paper's basic claim is a simple one: AI literacy is not a subcategory of digital literacy, it is not a buzzword to be nodded at in a placement brochure, and it deserves to be treated as its own, separately measurable dimension of employability.

We build this argument in four steps. First, we situate the problem within the broader human-capital and automation literature to establish why skills-based employability frameworks need periodic rethinking in the first place. Second, we situate AI literacy against the established employability and digital-literacy literatures to show where it fits and where it does not. Third, we connect it to career adaptability (Savickas & Porfeli, 2012), because we think the strongest case for treating AI literacy as distinct rests on exactly the adaptive, rather than static, quality that makes it hard to teach once and be done with. Fourth, we propose a four-part internal structure for the construct and sketch what a future measurement instrument would need to capture, while flagging honestly where the whole idea risks becoming precisely the vague buzzword it is trying to move past.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

This section draws on six overlapping bodies of work human-capital and automation research, employability theory, career adaptability, digital literacy, technology-acceptance modelling and the recent AI-literacy literature because no single tradition, on its own, gives a

full account of what we are trying to name.

The Shifting Ground: Human Capital and Skills in an Automating Economy

Becker's (1964) human capital theory treats skills and knowledge as a form of investment that individuals make in themselves, yielding returns in the labour market much as physical capital yields returns for a firm. The theory has aged well in one specific sense: it never assumed the relevant skill set was fixed, only that investing in whatever skills the market currently rewarded was rational. What has changed is the rate at which the reward structure itself moves. Autor's (2015) influential analysis of workplace automation argues that

technology has historically not eliminated employment so much as it has reshuffled which tasks within a job are performed by humans versus machines a reshuffling that tends to hollow out routine, codifiable tasks while leaving tasks requiring judgment, negotiation, and adaptability comparatively protected. Generative AI fits this pattern unusually well, and does so specifically at the entry level,

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where the compressed task ladder problem described elsewhere (Eloundou

et al., 2023; Brynjolfsson et al., 2023) is most acute. The practical upshot for this paper is that if the skills economies reward are shifting towards judgment and adaptability rather than routine execution, then an employability framework that does not explicitly name a competency for navigating exactly that shift is missing something the underlying economics already predicts will matter.

Employability as a Multidimensional Construct

Employability research has, for a long time, resisted being reduced to a single skill or trait. Hillage and Pollard's (1998) early policy-oriented framework treated employability as a combination of assets (knowledge, skills, attitudes), the ability to deploy those assets, the way they are presented to employers, and the context personal circumstances and labor-market conditions in which all of this plays out. Fugate et al. (2004) pushed this in a more psychological direction, defining employability as a form of proactive adaptability comprising career identity, personal adaptability, and social and human capital. Yorke's (2006) widely used definitional review is careful to distinguish employability itself a set of achievements and

attributes from employment as an outcome, a distinction worth preserving here because AI literacy, on our account, is squarely a matter of the former rather than a guarantee of the latter.

Tomlinson's (2012) review of the conceptual and empirical themes running through this literature usefully synthesizes these strands into a picture of employability as psychosocial capital human, social, cultural, and identity-related resources that a graduate can mobilize and present strategically. Clarke's (2018) more recent capital-based reworking of graduate employability makes a similar move, arguing that human capital (knowledge and skill) only translates into actual labor-market outcomes when combined with social capital (networks), cultural capital (the ability to read and perform within a professional context), and identity capital (a coherent, adaptable sense of professional self). Van der Heijde and Van der Heijden

(2006) add a further, and for our purposes especially relevant, dimension: anticipation and optimization, defined as the capacity to prepare for future changes in one's work and environment in a personally and professionally creative manner, rather than adapting only after the fact. What is useful about reading these frameworks together, rather than picking one, is that none of them was built around a single static skill set. They were built, from the start, to

accommodate a labor market that keeps moving. That is precisely the feature we want to lean on: if employability has always been partly about anticipating and adjusting to change, a technology that changes as fast as generative AI does is not a strange edge case for these

frameworks to absorb it is close to the central case Van der Heijde and Van der Heijden's anticipation/optimization dimension was designed for.

Career Adaptability and Career Construction Theory

Savickas's (2005) Career Construction Theory (CCT) treats career development not as the discovery of a fixed vocational fit but as an ongoing, narrative process in which individuals actively construct and adapt their professional identity across transitions. Savickas and Porfeli's (2012) Career Adapt-Abilities Scale operationalizes the theory's central adaptability construct across four resources: concern (orientation toward one's future), control (a sense of ownership over shaping that future), curiosity (exploring options and possibilities), and confidence (belief in one's ability to execute chosen paths). The construct's empirical standing is not merely theoretical assertion; Rudolph et al.'s (2017) meta-analysis of career adaptability research finds consistent relationships between adaptability resources and a range of adapting responses and adaptation outcomes across dozens of independent samples, which gives us reasonable confidence in borrowing the construct rather than treating it as an unproven metaphor. We as

researchers think these four resources map onto AI-related career behaviour with unusual precision, almost more cleanly than they map onto some of the contexts the scale was originally validated against. Concern shows up as a student's active tracking of how AI is reshaping their intended field, rather than treating it as background noise. Control shows up as a felt sense that one can choose how to position oneself relative to the technology, rather than being simply

carried along by it. Curiosity shows up in active experimentation with new tools as they appear. And confidence shows up as the belief that one can keep adapting, tool release after tool release, without the ground permanently shifting out from under them.

Digital Literacy: A Precursor Concept, and a Cautionary Tale

It is worth being honest about how much of this argument is genuinely new and how much is a variation on an older theme. Gilster (1997), who coined the term “digital literacy” in something close to its modern sense, defined it broadly as the ability to understand and use information from a variety of digital sources already, even then, more than a narrow tool- operation skill. The cautionary tale comes from Ng (2012), whose empirical work punctured a comfortable assumption that has aged particularly badly: that so-called “digital natives” young people who grew up surrounded by digital technology are automatically digitally literate simply by virtue of exposure. Ng found this assumption did not hold; technical comfort with a device did not translate reliably into the cognitive, information-evaluation, or social-ethical dimensions of digital literacy without deliberate instruction. We think the same cautionary point applies, probably with even more force, to AI literacy. A student who has used a

generative AI chatbot daily since adolescence is not, by that fact alone, critically or ethically literate about it, any more than frequent smartphone use in adolescence guaranteed the broader digital literacy Ng was investigating. If institutions repeat the digital-natives assumption in AI form assuming familiarity implies competence they are liable to repeat the same gap Ng identified, at a moment when the stakes of misplaced trust in a tool's output are considerably higher than they were for ordinary web literacy.

Technology Acceptance and the Limits of Adoption Models

A separate literature, largely from information systems research, has spent several decades modeling why people adopt new technologies in the first place. Davis's (1989)

Technology Acceptance Model (TAM) proposed that perceived usefulness and perceived ease of use jointly predict whether a person adopts a given technology, and the model has been validated and extended across an enormous range of settings since. Venkatesh et al. (2003) broadened this further with the Unified Theory of Acceptance and Use of Technology (UTAUT), adding performance expectancy, effort expectancy, social influence, and facilitating conditions as joint predictors of adoption and continued use. These models are useful to us mainly as a foil. They are very good at explaining whether a student will start using a generative AI tool and, on the evidence of casual observation in almost any classroom today, adoption is close to universal and therefore not the interesting variable anymore. What TAM and UTAUT do not address, because they were never built to, is whether a person uses the tool with good judgment once adopted: whether they know when its output is unreliable, when using it at all

is inappropriate, and when their own reasoning should override it. That gap is precisely where we think AI literacy, as an employability competency rather than an adoption outcome, needs to do its work.

What AI Literacy Actually Means

It helps to be precise here, because “AI literacy” gets used loosely enough in practitioner conversation that it risks meaning everything and therefore nothing. Long and Magerko's (2020) competency-based

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definition is useful precisely because it resists that looseness: they define AI literacy as a set of competencies enabling a person to critically

evaluate AI technologies, communicate and collaborate effectively with them, and use them as tools in a range of contexts spanning knowledge of what AI is and how it works, through to the ethical and societal considerations that surround its use. Ng et al.'s (2021) exploratory review of the emerging AI-literacy literature finds a broadly convergent picture across independent research groups: definitions cluster around knowing, applying, evaluating, and ethically reasoning about AI, rather than around any single technical skill. Kong et al.'s (2021) evaluation of an AI-literacy course delivered to university students from diverse academic backgrounds is worth flagging separately, because it demonstrates the competency is not merely theorized but already being piloted in higher education, with encouraging early evidence that non-technical students can meaningfully develop it given structured instruction. Note what none of these definitions reduce to: AI literacy is not merely the ability to write a good prompt, and it is not merely comfort with a particular interface. It is closer to a form of critical fluency knowing enough about how these systems tend to fail to know when to distrust them.

Positioning AI Literacy as a Distinct Employability Dimension

Boundary Conditions: AI Literacy Versus Digital Literacy Versus Technical AI Skill

Three things get conflated here that are worth pulling apart. Digital literacy, in Gilster's (1997) broad sense, is largely about comfort and competence with digital tools and environments in general it is a floor, and most entering students already clear it, even if Ng's (2012) findings suggest that floor is less secure than assumed. Technical AI skill, at the other extreme, means something closer to building or fine-tuning models a specialist, largely technical competency that most management students neither need nor are seeking. AI literacy,

as we mean it here, sits in between, and is arguably more demanding than either in one specific

respect: it requires ongoing judgment about a tool whose behavior is not fully predictable even to the people who build it. You do not need judgment to use a spreadsheet correctly; a formula either works or it does not. You do need judgment to decide whether an AI-generated market analysis is trustworthy enough to act on, and that judgment does not get easier just because you have used the tool many times before which is also, incidentally, why the technology-acceptance models discussed above stop being useful at exactly the point where this paper's real interest begins.

A Four-Part Structure

We propose that AI literacy, understood as an employability competency, decomposes into four related but distinguishable parts.

Operational AI literacy is the practical ability to use AI tools effectively for a given task prompt construction, tool selection, basic workflow integration. This is the part most existing corporate training already covers, and the part most likely to have a short shelf life as interfaces change.

Critical AI literacy is the capacity to evaluate AI output for accuracy, bias, and appropriateness to notice when a plausible-sounding answer is subtly wrong, or when a recommendation reflects a training-data default rather than the actual situation at hand.

Ethical AI literacy is judgment about when AI use is appropriate at all, including transparency about its use, awareness of data and privacy implications, and sensitivity to situations, where relying on AI output would itself be a professional or ethical lapse.

Adaptive AI literacy is the ongoing capacity to update the other three as the technology itself changes this is the resource most directly tied to career adaptability, and the one we think does the most work in justifying AI literacy as its own employability dimension rather than a rebadged version of digital literacy.

Of these four, adaptive AI literacy is, in our view, doing the real conceptual work. Operational,

critical, and ethical AI literacy could, in principle, be taught as a fixed curriculum and assessed like any other competency, in much the way Kong et al.'s (2021) piloted course attempts.

Adaptive AI literacy cannot be taught that way, because its object keeps changing; it can only be cultivated as a disposition, which is exactly the language Career Construction Theory already has available for this kind of thing.

Toward Measurement: What a Future Instrument Would Need to Capture

This paper does not propose a validated scale that is a separate undertaking, and one we intend to pursue as a dedicated follow-up study. But it is worth sketching, even briefly, what such an instrument would need to capture if it is to measure AI literacy as an employability competency rather than as narrow tool proficiency. It would need items addressing each of the four sub-dimensions above rather than collapsing them into a single score, since a respondent

could plausibly score high on operational fluency while scoring low on critical or ethical literacy and that gap is itself diagnostically useful information for a career-services office rather than noise to be averaged away. It would also need to avoid anchoring items to any single named tool, given how quickly today's dominant platform becomes tomorrow's legacy system, a lesson learned, somewhat painfully, from earlier digital-literacy instruments that aged out of

relevance within a few product cycles. It would benefit from being validated against the existing Career Adapt-Abilities Scale (Savickas & Porfeli, 2012), to test empirically whether adaptive AI literacy is really tracking general career adaptability, as we suspect, or whether it turns out to be something more independent than our framework here assumes.

Implications for Career-Development Cells and Employers

For university career-services offices, the practical implication is to stop treating AI-tool training as a single onboarding session and start treating it as a recurring, cyclical part of employability development closer to how communication skills or interview preparation are

handled, revisited across a program rather than delivered once and checked off. For employers, particularly those involved in campus recruitment, the implication is that interview and case formats could usefully probe critical and ethical AI literacy by directly asking a candidate not simply whether they use AI tools, but how they decide when to trust an output, and where they have caught one being wrong, rather than inferring AI competence indirectly from the polish of a submitted deliverable, which recent work on career signal crafting suggests is an increasingly unreliable signal in its own right.

DISCUSSION: TENSIONS AND OPEN QUESTIONS

We want to be honest about the biggest risk this paper runs, because it is the same risk we opened by criticizing. “AI literacy” could very easily become exactly the kind of vague, feel-good competency label we accused existing employability checklists of already being weighed down by a box ticked in a placement brochure, disconnected from any real measurement or teaching practice. The four-part structure proposed above is our attempt to guard against that by giving the construct enough internal detail to be operationalized rather than merely gestured at, but a framework on paper does not guarantee careful implementation, and we do not have a strong answer to what happens if institutions adopt the label without

adopting the substance behind it.

A second, genuinely unresolved tension concerns equity. Access to advanced AI tools, reliable high-speed internet, and prior exposure to

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AI-assisted workflows is not evenly distributed across students, even within a single cohort, let alone across institutions of different

resource levels. If AI literacy becomes a recognized, rewarded employability dimension

without deliberate institutional effort to close this access gap, it risks becoming one more axis on which existing advantage quietly reproduces itself under a new name a concern that echoes similar equity flags raised elsewhere in the career-signal-crafting literature this paper's authors have developed in parallel work, and that also echoes Clarke's (2018) point that human capital alone rarely translates into employability outcomes without the social and cultural capital to deploy it.

A third tension is more conceptual than practical: we have argued that adaptive AI literacy is what makes this construct distinct from ordinary digital literacy, but we have not fully resolved whether adaptive AI literacy is truly a separate competency or simply general

career adaptability (Savickas & Porfeli, 2012) expressing itself in a particular domain. Rudolph et al.'s (2017) meta-analytic evidence for the breadth of career adaptability's predictive reach makes this an especially live concern; it is possible that future empirical work will find the two are not meaningfully separable that a student high in general career adaptability is, more or less automatically, also high in adaptive AI literacy, in which case the added conceptual machinery proposed here would need to be trimmed back rather than defended.

LIMITATIONS

This is a conceptual paper, and its four-part structure, while grounded in the literatures reviewed above, has not been empirically tested. The proposed sub-dimensions are, at this stage, analytically derived rather than data-driven, and the measurement agenda above describes what an instrument would need rather than providing one. As with any new

competency framework, its ultimate value will be judged by whether it can be operationalized into something career-services practitioners and employers use, rather than by the internal coherence of the argument alone.

CONCLUSION

Employability frameworks have always had room for change that is arguably their whole point but generative AI is testing that room in a way most existing checklists were not built to absorb gracefully. Treating AI literacy as a fourth, distinct employability dimension,

structured around operational, critical, ethical, and adaptive components, gives career- development cells and employers a more precise vocabulary than either ignoring the issue or flattening it into an existing digital-literacy line item. The adaptive component is where we think the real and lasting competency lives, since it is the one piece of this framework that cannot be taught once and considered finished. Whether that claim holds up is, as with the rest

of this paper, a question for the empirical work that should follow it.

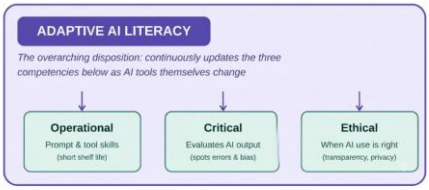


Fig. 1. Proposed four-part structure of AI literacy.

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