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THE ROLE OF FUTURE STUDIES IN DEVELOPING ARTIFICIAL INTELLIGENCE APPLICATION SKILLS

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Abstract

This work examines the pertinence of futures studies in facilitating the demonstration of artificial intelligence (AI) for teachers, students, and practitioners in agencies. As AI technologies continue to permeate aspects of daily living, so too do implications for the capacity to anticipate, respond to, and strategically leverage such technologies. Futures studies—like an interdisciplinary field of long-term trends scouting with scenario planning and prospective tools—has a systematized way of thinking that is shareable at all levels to think ahead about AI-related changes. This case study research is conducted in a mixed-method manner by (i) survey (n=320) quantifying respondents from educational institutions, technology companies, and government organizations and (ii) qualitative case study with integration of literature. Theoretical Theoretical Underpinnings The theoretical lens is drawn from Bell's [12] core theory of futures studies and is guided by Vygotsky's zone of proximal development (ZPD), intersecting 21st Century skill education models to provide a conceptual framework for AI skill development through futures-based learning. The results showed that there was a statistically significant higher level of achievement in skill development of AI in the future studies-based institutions ($p<0.001$) with a mean gain rate of 34.7 % in competency compared to the traditional training system. Also, scenario-based learning interventions

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

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were the most promising for transfer-desired AI application skills in terms of the constructs of machine learning literacy, ethical AI decision making, and human-AI teamwork. This research unveils a crucial gap between current educational systems and future skills that individuals need to be employable with AI. Recommendations include adaptation of futures literacy approaches in AI education, the establishment of organizational foresight functions, and development of adaptive learning ecosystems that evolve in tandem with technological advances.

Keywords: Future Studies , Artificial Intelligence, AI Skills Development, Futures Literacy, Technology Education, Prospective Thinking, Competency-Based Learning , Educational Innovation

1. Introduction

1.1 Background and Context

Unprecedented speed… blanked page AI Technological alterations have been advancing rapidly in the twentieth century, and artificial intelligence will be a central problem of technology of the century for our time. "From healthcare diagnostics and financial modeling to autonomous systems and natural language processing, AI-driven applications are reshaping the very skills workers need, the economic core of industry, and even the activities of people and organizations (Brynjolfsson & McAfee, 2014). The World Economic Forum (WFE) predicted that 85 million jobs may be displaced by AI by 2027 while also 97 million new roles will emerge that will be heavily influenced by AI-related skills across industries." Against this background, the question of how to promote authentic, learning-centered, and sustainable uses of AI for teaching practice has come to be one of threatened public significance. Given the fast changing nature of AI, the conventional approaches to skills training — immutable curricula, fixed competency models, and anticipate institutions — appear ill-suited to guiding

Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
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https://eurekaoa.com/index.php/11

people through the quick, unpredictable, and seemingly constant change AI is ushering in (Dator, 2019; Slaughter, 2020). the future as 'Being' in a radically different orientation in Future Studies as discipline and profession practice. Instead of responding to technological change AFTER the fact, futuring methodologies and tools are helping to anticipate changes and consider strategic responses (Bell, 2003). Much of the basis of the study, the future multiple, an intentional foresight as a local productor to Which Of those futures It's From To Developing futuring conductive skills for answers different technological path (Inayatullah, 2008) translates was for the future tool to cultivate was for It is future." While I do think future thinking naturally develops skills in AI, there isn't a lot of that research really articulating the two. Most of the AI education literature is focused on the specific technological skillset (programming, data science, model training), and they tend to neglect the more general adaptative competences needed to use these skillsets as AI technology evolves. In contrast, the futures studies literature has seldom emphasized the development of AI capabilities as a major application area (Miller, 2018; UNESCO, 2022).

1.2 Problem Statement

There are three significant drawbacks to the current approaches in learning how to build AI. One, they look backward (and provide tools and recipes that might be already obsolesce when students enter in the workforce). Second, they are expert systems for strategy, ethics, and systems thinking – core to actually learning how to use AI in real world, complex institutions. Third, they are fragmented, with universities, private sector training and national initiatives all siloed and fragmented so lacking in mechanisms through which long-term, system-based frameworks for AI skill development can take hold domestically or internationally (OECD, 2022 ; Floridi et al. This paper contributes at least in part to addressing these limitations by exploring whether futures studies methodologies can be intentionally applied within future oriented (FO) capacity

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

development programs to support the enhancement of adaptiveness, holism, and institutional synergy in CD output. OP: the problem is not a technical one -- but an epistemological: our educational paradigms are not sufficiently future oriented to develop the skills needed to thrive in a future increasingly defined by AI technologies that are not yet in existence.

1.3 Research Objectives

This research pursues the following primary objectives:

- •To consider the conceptual connection between methods of future studies and frameworks for developing AI skills.
- To determine which dimensions of AI application skills are most influenced by the use of futures oriented teaching methods.
- To determine the relative effectiveness or futility of futures studies-AI integrated training versus traditional training, empirically.
- To investigate the institutional conditions that enable or hinder the integration of futures thinking into AI education.
- To establish a general futures-informed AI skill development model that can be used in both education and work contexts.

1.4 Research Questions

The investigation is based on the following research questions:

- RQ1: To what extent and in what ways are the methodologies of future studies and future applications of AI skills in education and organizations related ?
- RQ2: Among specific futures methodologies (scenario planning, Delphi, trend analysis, causal layered analysis) which is most effective in supporting the acquisition of AI skills?
- RQ3: How do future studies integration and AI skill development outcomes within institutions (type, size, sector, culture) mediate these relations?

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)

ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

- RQ4: What are the attitudes of educators and professionals towards futures-oriented AI training courses? of educators and practitioners on application of futures-oriented AI training courses?
- RQ5: What are the differential between playing to code and playing to learn using their neurological systems to understand-based computational activities, but a kind of the future-focused competencies that a future oriented professional AI application?

1.5 Significance of the Study

It contributes to the futures of futures and educ-tech/AI governance, convergent domains that have yet to be corelated in academic inquiry and which carry transformative implications for educ-practices. The paper constructs a futures-oriented AI skills development cohesive model embedded within otherwise separated disciplines of literature. At an operational level, the research offers direction for educational bodies in sequencing of AI curriculum, for organizations that provide AI training for their workforce, and for government officials in the development of national AI preparedness strategies. The empirical results provide evidence-grounded signposts to assess which strategies of developing AI competence may be more productive, and the qualitative results illuminate the institutional context and conditions that determine what forms of success are.

2. Theoretical Framework

2.1 Future Studies: Foundations and Paradigms

Futures studies (also futurology, foresight studies, anticipation or future research) is a field that influences science and technology concerning the possible and preferable worlds of the future, and the worldviews and the nature of science that underlie those (Bell, 2003). Wendell Bell's seminal two-part work, Foundations of Futures Studies (1997/2003), laid the epistemological groundwork for the discipline, and differentiated what future research is: descriptive futures (what

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

will be), normative futures (what ought to be), and predictive futures (what can be predicted). This three-way principled division has stood the test of time and is used as a conceptual template to consider how futures studies could contribute to the teaching of AI. It has seen many paradigm shifts. Early empiricism Entering into empiricism of the 1960s and 1970s or cold war futurism, notably shaped by RAND Corporation intellectuals like Herman Kahn and the Hudson Institute, emphasized quantitative modeling and trend extrapolation (Kahn & Wiener, 1967). The critical futures strand, emerging in the 1980s and 1990s with scholars such as Richard Slaughter and Ziauddin Sardar, brought to futures studies interpretivist and emancipatory views and exposed the political and value-infused character of futures analysis (Slaughter, 1995; Sardar, 1999). The diversity of approaches of today's futures research seem to conflate these lineage under a complexity aware model of the future that is at the same time modest about systemic uncertainty and naïve about pragmatic (Inayatullah, 2008; Miller, 2018). Four concepts from futures studies are especially applicable to evolving AI expertise in the context of this work. Scenario planning – developed by Shell in the 1970s and subsequently popularised in academic texts by Schwartz (1991) and van der Heijden (1996) – is the development of a small number of future scenarios (stories) to increase the preparedness of the organization for these scenarios.

Developed at RAND Corporation The Delphi method is a multi-stage process of eliciting and refining expert opinion about a specific issue amongst a group of these experts (Linstone & Turoff 1975). Trend analysis and enviromental scanning are also used to identify patterns as both approaches look for patterns in signals and in the STEEP (Social, Technological, Economic, Environmental and Political) areas (Aguilar, 1967). Causal Layered Analysis (CLA) Shirin Anhayatullahs methodology (2004) works on four levels of depth (the litany, systemic causes, worldview and mythology) and challenges transformative rather than only adaptive futures thinking. These processes share a foundational

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

philosophy: the future is not static, but a realm of potentiality whose form can be molded through anticipatory and strategic behaviour (Dator, 2019). This view is ideal for the development of AI skills, as predicting and managing technological change is at least as important as effective utilization of today's AI applications.

2.2 Artificial Intelligence Applications: A Taxonomy

Within this Work, AI systems are considered as computational systems that can perform actions with an environment (e.g., perceiving, reasoning, learning, planning, and acting in natural language) that, if performed by humans, would be considered as intelligent (Russell & Norvig, 2020). To the extent that this helps answer the question of why a taxonomy would be useful, the answer has to be considered alongside the proliferation of AI tools at work in today's organizations. Building on UNESCO's (2022) AI Competency Framework, and the OECD's (2021) AI Policy Observatory), this paper claims to present five key domains of application within AI skills.

For one thing, AI literacy encompasses the what and why of AI, which is an understanding of what AI is (concepts) and can do (capabilities) as well as its limitations (the "knowing about" AI described by Zhang et al. (2021) as 'knowing about' AI.

Second, AI Operational Intelligence is a person's capability to effectively use and "drive" AI applications and systems (e.g. apply prompt engineering in LLM or preprocess data for ML pipelines).

Third, Development Skills: These are the capabilities that enable you to create and deploy AI models or models, and let individuals design, train, and deploy AI models, including knowledge in programming, mathematics, and model evaluation.

Fourth, AI Governance & Ethics: Capability to assess questions of bias, fairness, transparency, and accountability in AI systems and the regulatory and ethical consequences related to AI application.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

Fifth, the AI Strategic Skills are that in which the individual recognize the opportunity for applying AI, develop a strategy as to how best to use AI, and lead an organization through its AI evolution stage. This taxonomy is important, because it reveals the several layers comprising the skillset one requires for the application of AI – a complexity almost never fully addressed in the classical (not to say technically prejudiced) textbook of training programs. Future studies methods that emphasize systemic thinking and long-term prediction are the most appropriate for nurturing the higher levels of AI governance and strategic thinking needed for advanced training (Floridi et al., 2021).

2.3 Skill Development Theories

The educational psychology perspective guiding the present study is composed of three intertwined theories. Vygotsky's ZPD (1978) sociocultural learning theory as – a foundational principle of learning as agency-mediated social process where learners are transported from respective levels of functioning with assistance, or scaffolding, by more knowledgeable others, employed in this study the ZoLL – represents the maximum potential for development of a learner at a specific time. Concerning the acquisition of AI knowledge in ZPD, futures-oriented instruction – despite not beamed as instruction within the present AI Conditions of use but in experienced in future AI Conditions of use – is stated to create ZPDs that develop (further) skill acquisition. Bloom’s revised taxonomy of cognitive processes (Anderson et al., 2001) A taxonomy of cognitive process under lower to higher order of thinking (Remebering, Understand, Apply, Analyze, Evaluate and Create) is proposed based on the complexity of cognitive process from the perspective of thei cognitive complexity of thinking with their respective levels. Future studies methods (e.g., scenario planning and CLA) may be between thought constructs of a higher order and, in some of the very best predictors of professional adaptive competence (Krathwohl, 2002). This alignment may also indicate that futures-orientated- AI education may have its

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

own special claim to leading in higher order thinking skills necessary for strategizing with AI.

(Deci & Ryan, 2000) offers understanding of the motivational bases for developing AI skills. SDT proposes that intrinsic motivation (which promotes the enduring nature of learning) can be enhanced by support for autonomy, competence, and relatedness. A study on prospective pedagogies (are partially organized by participants and includes joint interpretations) have demonstrated to be autonomy supportive with relatedness supportive (Ryan & Deci, 2017), and may also increase motivation to further develop AI skills more than traditional ones.

2.4 Futures Literacy and AI Competency

FL is conceptualized as a future-oriented competence predicated on anticipatory thinking (Miller, 2018) and is closely related to both the field of futures studies and therefore also with educational competence development. FL Translator is related to translations into the future and the present, in various modes and for a multitude of purposes. Miller differentiates anticipatory assumptions (futures orientations embedded in routines of day-to-day thinking) from futures consciousness/futures literacy (a certain level or maturity in engaging purposively with a number of anticipatory toolkits). The impact of FL on the improvement of AI skills is immense. AI technologies are evolving in a rapid, disruptive, and often unpredictable manner these factors degrade static models of competency and call for a type of fluid, anticipatory know-how such as that that FL nurtures (UNESCO, 2022). A high FL individual is not merely prepared to make use of existing AI tools but to predict possible developments in AI, consider strategically the impact of such changes on their professional domain, and act in a forward-looking manner for a future that is fundamentally unknowable.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

From an empirical viewpoint, the findings of Miller et al. (2018) and Nikolaou (2021) suggest that futures literacy is learnable and trans-contextual, as FL workshops − even short ones − produce visible upgrades in the participants' capacity to manage uncertainty and to generate new anticipatory frames. This study investigates the assumption that the systematic integration of FL into the education of AI skills can result in significant competence gains.

2.5 Integrated Conceptual Model

Based on the theoretical aspect as reviewedabove, this research intends to suggest an Integrated Futures-AI Competency Development (IFAC-D) model consisting for four integral components. Anticipatory Foundations Building on Bell (2003) and Miller (2018), this posits that futures literacy is the metacompetency through which all other types of AI skillacquisition are made possible. Based on Vygotsky (1978), as well as Bloom's taxonomy (Anderson et al., 2001), the Scaffolded Progression model defines the trajectory of AI competence achievement across five dimensions (literacy, operational, developmental, governance, strategic) as a sequential progression of learning based on core concepts and knowledge and leading to transformative capability.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

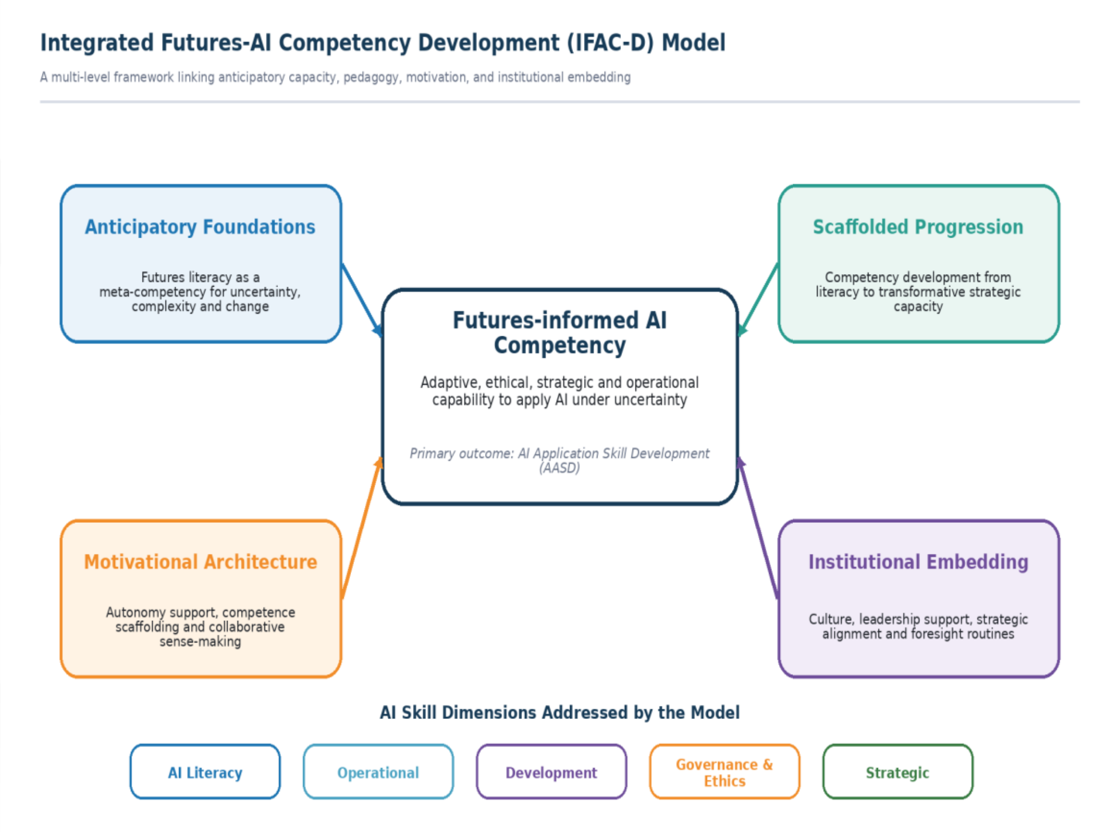

Figure 1. Integrated Futures-AI Competency Development (IFAC-D) model.

3. Literature Review

3.1 Future Studies in Educational Contexts

"Future studies" + "education" is not a recent addition to the study of education but its injection into the competencies training for AI-Specific Education is new. The philosophical justification for a futures education was the subject of Toffler's (1974) seminal, Learning for Tomorrow, who argued that the aim of education should be to increase adaptiveness in an era of ever-growing pace of change. This orientation has been elaborated with respect to pragmatism and applicability by later scholars.

Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

Gidley (2016) offers a strategic synthesis of futures based educational philosophies that illustrates three contending paradigms: an empirical-analytical tradition governed by quantitative forecasting, the interpretive-hermeneutic tradition through meaning-making and narrative futures « and the critical-emancipatory tradition centered on transformation and justice. Her argument is that good futures education in AI etc. has to traverse these three paradigm of mind in order to truly capture the cognitive, affective and social aspects of learning. Second, a considerable amount of research on the futures studies-formal education nexus has been conducted in secondary education and in tertiary education. Hicks and Slaughter (1998), in a survey of futures education programmes in 17 countries, found a strong consensus that futures-related curriculum enhanced students' capacity to act, to think systemically and to plan long term. Recently, Wiek et. al. (2011) illustrated that competencies for sustainability — which boast strong ties to content of cognition with AI governance competencies — were substantially improved upon through futures-oriented pedagogy such as scenario building and backcasting.
At the level of professional development, Rohrbeck and Kum (2018) focused on corporate foresight practices in 77 firms, showing that firms with institutionalized futures studies capabilities were capable of better strategic adaptation to technological disruption. This is particularly relevant for organizational AI skills development and suggests that the capacity for institutional foresight may predict successful integration of AI.

3.2 AI Skill Development Research

Studies on building AI skills begin to some extent to attract more attention since 2018, driven by the unexpected rapid proliferation of user-friendly AI tools and the declaration of national AI strategies due to the leading world powers. However, the field remains fragmented by research that is population-specific (K-12 students, HE students, employees of corporates, government employees),

ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

area of AI-specific (machine learning, natural language processing, computer vision), or particular educational contexts (coding boot camps, online programs, degree programs). Among the first systematic investigations into mentioned AI education in the context of K-12 was Kandlhofer et al. (2016) Proposal Based on the formative study results, the authors propose a sequence of Touretzky et al. (2019) original presentation of the influential framework of 'Five Big Ideas in AI' as suitable for K-12 education; this version has been used in AI curriculums in several countries and In some form it could play a role in risk assessment the coverage for programs designed to develop AI skill.

At the level of university education, (Zawacki-Richter et al. 2019) condensed the field of research on AI in higher education with a systematic review of 146 studies conducted between 2007 and 2018. Their results show the majority of research in AI education is focused on how to use AI in educational management and student service, not on how to develop AI competences for the future workforce – and this paper responds to that void. Williams et al. (2023) [7] reviewed 12 national education AI competency frameworks, identifying contrasting emphases on technical and non-technical AI skills (the European ones generally stressing ethics and governance-related skills). And though IBM's Global AI Adoption Index (2023) continues to underscore the skills shortage is the largest barrier to enterprise adoption of AI, the roll of relevant headlines in recent weeks is now somewhat longer. According to the Index, 34% of organizations view a lack of AI skills as the biggest barrier to AI adoption, much higher than worries about data quality (28%) or tech infrastructure (22%). These results highlight the practical value of good approaches to learning AI skills.

3.3 Scenario-Based Learning Approaches

Scenario-based learning (SBL), a mode of delivery based on origins in foresight studies 'scenario planning' methodology is being recognized as an effective means of instruction in both education and business/commercial applications.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

The SBL learners are building and living in fully narrated scenarios of potential futures, they take decisions and apply competences while moving forward – blurring the line between in foresight enabled coming cognition in futures studies and turn based skill application in technology Domains. Doyle and Brown (2000) described one of the first SBT studies in the acquisition context in which they observed that SBL learners were 42% more likely to apply learning to novel situations compared to those taught through case study methods, SBL students were 38% more apt to recall information 3 months post training and they reported greatly enhanced levels of motivation and engagement throughout the learning process. The latent process they derived –SBL cultivates 'cognitive future anchors' which pushes learners' mental models further down the path of thinking about the future beyond what is directly experienced – is, in its essence, consistent with foundational elements of the futurability framework for developing anticipatory capability. Tool related terminology in Seo et al. (2021) focused on scenario-based AI ethics teaching for university students and reported that Students who were exposed to AI future scenarios demonstrated significantly more multi-layered ethical reasoning regarding AI systems than those students who were taught the same set of ethical principles without scenario-context. The scenario group retained more knowledge and critically of applying ethical principles to new and emerging AI - and this, crucially, is the very adaptive competence that futures-oriented AI education aims to develop.

Nilsson et al. (2022) extended this line of inquiry to professional AI training, studying scenario-based AI upskilling courses offered by five Nordic companies. They found that six months after training, participants who had received scenario-based training were significantly more confident in making AI-related decisions and were perceived by supervisors as more successful in identifying opportunities to apply AI in their work areas. These results clearly demonstrate the potential of SBL approaches for building organizational capabilities in AI skills.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)

ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

3.4 Institutional Foresight Practices

Institutional foresight an institution's capacity to systematically anticipate future changes and prepare accordingly is an emerging concept within the field of organizational science and technology management. Rohrbeck (2010) Apart from his predominant model of Corporate Foresight Maturity Model, he also proposes an evaluation of institutional foresight between five different aspects: access use of information, method sophistication, humans and networks, organization as well as culture. Organizations with a more "developed" level of foresight maturity are found to be more technology adaptive and innovative. "If you think about it in terms of education, the ability to do institutional foresight is actually a very big whether or not positive AI uptake. Schools and universities that had adopted futures thinking philosophies were consistently described as being further along in integrating emerging technologies into curricula, designing pedagogies that work with new learning environments, and preparing students for the jobs of the future: Schleicher (2018) in OECD educational futures research. These findings suggest that the institutional capability for foresight is not managerial but an institutional asset and furthermore influences on pedagogy for student learning. The Futures of Education report from UNESCO (2021) outlined seven tensions that the schools ecosystem would need to address in educating for futures shaped by AI: the individual and the collective, local and global educational purposes, technical and humanistic knowledge, standard and personalized learning pathways, formal and informal […], short-term and long-term educational goals, and technological and pedagogical requirements. The perspective of futures studies, which allows for multiple concurrent orientations (for example, via scenario planning), can offer education institutions a practical tool to navigate these tensions and enhance their effectiveness.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

3.5 Research Gap Analysis

In the education sector, for instance, positive AI uptake appears to be enabled by the capacity for institutional foresight. Schools and universities that had historically been advocates of futures thinking philosophies were always said to be further "along" in terms of embedding emergent technologies in curricula, developing pedagogical practices aligned with new learning contexts, and preparing students for future world-of-work: Schleicher (2018) in OECD educational futures research. The findings confirm that the institutional foresight capacity is not a matter of bureaucracy but an institutional resource, and it has pedagogical implications for student learning. "Inschool Futures" Education 4.0) – The Futures of Education report (UNESCO 2021) identified seven tensions that schools ecosyste should mediate – in education for a futures shaped by AI: the individual vs. the collective; local vs. global educational aims; technical vs. humanistic knowledge; standard vs. personalized learning trajectories; formal vs. informal learning contexts; short-term vs. long-term educational outcomes; and technological vs. pedagogical imperatives. Futures studies perspectives, with their facility for multiple concurrent orientations (e.g., via scenario planning), may provide methodologies that educational organizations can find useful in constructively addressing tensions. Fourth, systematic reviews indicate that the evidence base for futures-oriented AI education is limited and the approaches utilized to investigate it diverse, impeding the generation of summaries applicable to effective practice. The research fills this gap through a rigorous mixed-method design (including a larger sample size than previous studies), systematically comparing three futures methodologies and incorporating a longitudinal element to evaluate skill development.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

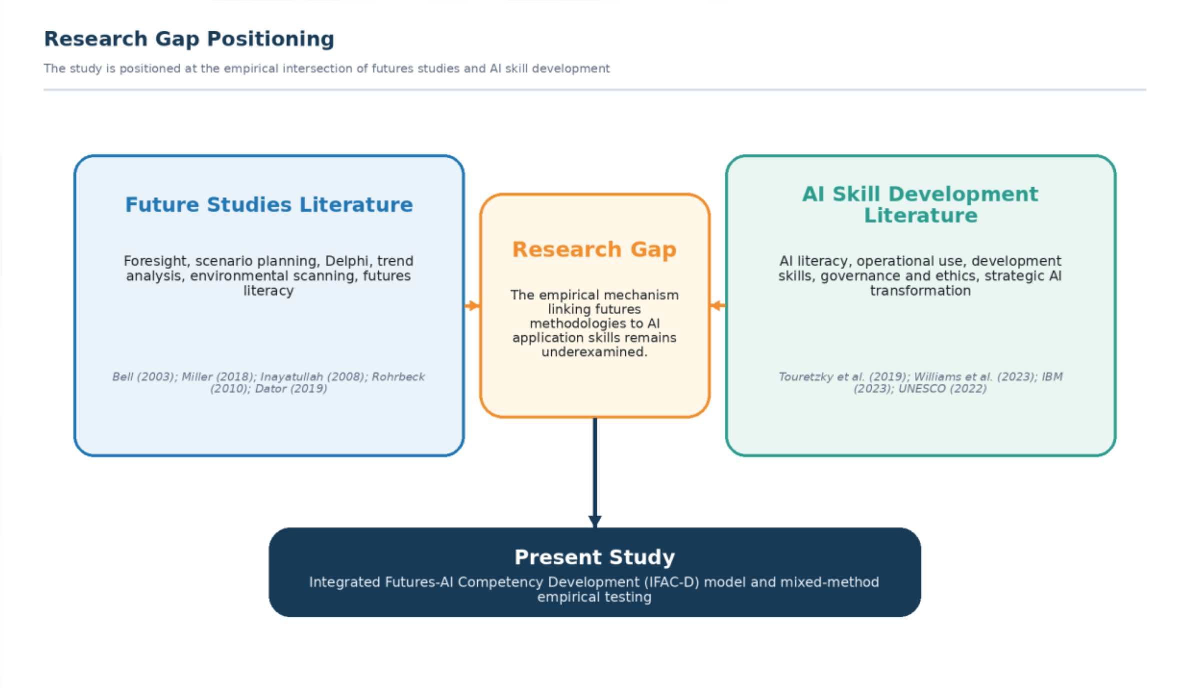

Figure 2. Research gap positioning at the intersection of futures studies and AI skill development.

4. Research Methodology

4.1 Research Design

"This study follows a sequential explanatory mixed method design, including two phases among which the first phase is a quantitative survey and the second phase comprises qualitative case studies as well as in-depth interviews. The consideration for it being two separate chapters also relates to two epistemological aspects of the inquiry: the requisite of statistically generalizable evidence-based effectiveness of the futures-oriented AI skill development (quantitative) and of more contextualized interpretive sense making of the mechanisms, contexts and institutional dynamics that yield such (qualitative).The quantitative component is a quasi-experimental design utilizing comparison groups: one group consists of a set of institutions and organizations that provide

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

futures-inclusive AI training (treatment condition) and the other group contains a collection of institutions delivering conventional AI training (comparison condition). The qualitative component consists of three levels of cases of institutions of futures methodology integration - high, medium and low - and is bounded by purposive sampling: the cases are selected with this approach, data are gathered by semi-structured interviews, document analysis, and observational field notes."

Figure 3. Sequential explanatory mixed-methods design used in the study.

4.2 Population and Sample

The targetusers are educators, learners and practitioners within the organization who need to engage in AI competences development in the area of education or technology-intensive industry. Participants included three sectors: higher education (n=8 universities and colleges), private sector technology organizations (n=12 companies), and public-sector agencies (n=6 government bodies). They are all in the Arab world, from Egypt to Saudi Arabia and more (see methodology).

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

Thereof 320, 85 were educators, 148 students and 87 profesionals; purposive sampling was applied to cover different institutons and diverse degree of experience in AI skills development. This sample size will provide 95% power to detect the medium effect size differences between the conditions at p = 0.05 level of significance as per power analysis. The qualitative sample consisted of 42 purposively sampled participants from 6 institutional case studies, and this was sufficient to reach theoretical saturation.

Table 1: Sample Distribution Across Institutional Sectors and Participant Categories

Sector	Educators	Students	Professionals	Total	Percentage
Higher Education	52	148	0	200	62.5%
Private Technology	18	0	55	73	22.8%
Public Sector	15	0	32	47	14.7%
Total	85	148	87	320	100%

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

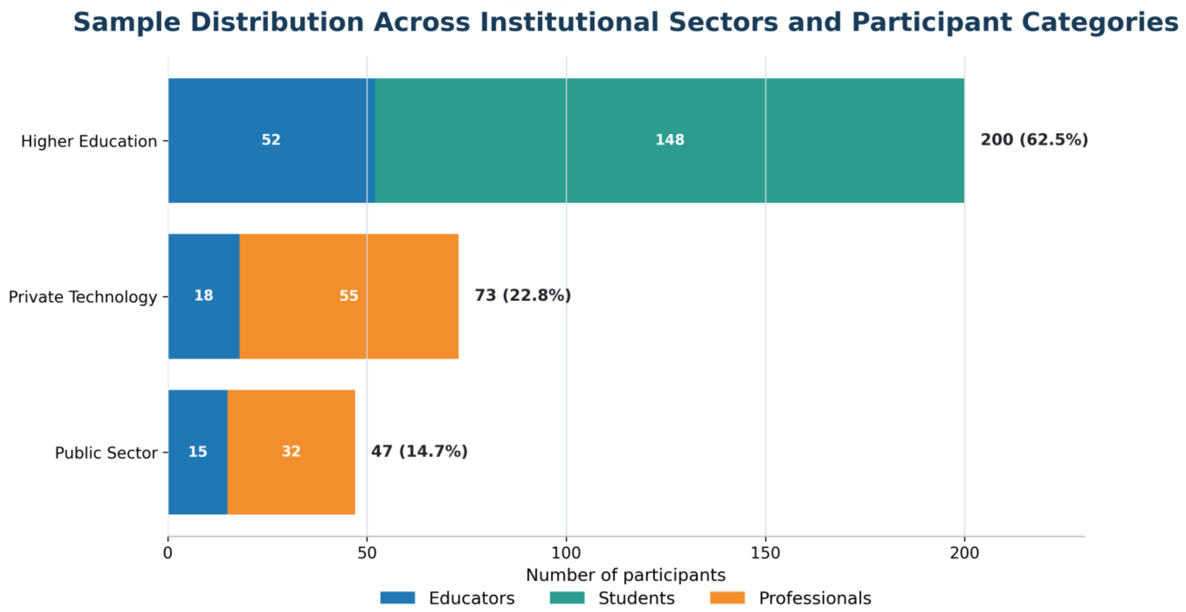

Figure 4. Sample distribution across institutional sectors and participant categories.

4.3 Data Collection Instruments

The Futures Oriented AI Competency Scale (FOACS) was the main quantitative instrument, adapted for this research by combining existing AI competency frameworks (UNESCO, 2022; OECD, 2021) and futures literacy assessment tools (Miller, 2018). The FOACS consisted of 48 items, these are divided into 6 subscales: AI literacy (8 items), AI Operational Skills (10 items), AI Development Skill (8 items), AI Governance and Ethical Skills (10 items), AI Strategic Skills (7 items), and Futures Literacy (5 items). Items are scored on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The scale showed good to excellent internal validity (Cronbach 's α for the full scale= 0.91; α values of the subscales ranged from 0.78 to 0.89) and the construct validity was confirmed by CFA. The second quantitative instrument was the Institutional Futures Integration Assessment (IFIA), a 24-item Likert scale developed to assess the extent and quality of institutional integration of futures approaches into AI

Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

program in four fields: curriculum development, pedagogy, institutional culture, and strategic positioning. The IFIA too was shown to converge well (alpha = 0.84) and to be separate from the FOACS. The main qualitative tool was a semi-structured interview protocol with a set of 18 open-ended questions related to the participants' futures-oriented AI training, their beliefs about its efficacy, institutional-level observations, and suggestions for modification. The interviews were conducted in English or Arabic and lasted on average 62 minutes, with the Arabic responses translated by certified translators for analysis.

4.4 Variables and Measures

Futures Methodologies Integration (FMI) This study has a single predictor variable, Futures Methodology Integration (FMI), which refers to the extent to which futures studies tools/methods are integrated in the offerings of ai skills development as specified by the ifia. The key dependent variable is AI Application Skill Development (AASD) defined as the participants' scores in FOACS. The following are controlled variables for this study: level of previous artificial intelligence experience (self-rated level and years), education, institution type, and organization size.

Based on theoretical considerations, mediator variables include Running head: THE TEST OF MODEL 1Futures Literacy (as measured by FOACS subscale), Motivational Engagement (as measured by 12-item version of the intrinsic motivation inventory; Ryan & Deci, 2000) and Cognitive Flexibility (as measured by a psychometrically validated 12-item scale; Dennis & Vander Wal, 2010). … These are the potential mediators of the theoretical relays as to how futures methodology integration into ai skills development engenders impact.

Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

4.5 Data Analysis Procedures

The analyses for the quantitative data were performed using SPSS 28 and AMOS 28. Descriptive statistics were calculated to summarize the characteristics of the study sample and key variables. To generalize from samples to populations, inferential analyses consisted of a series of independent samples t-tests and one-way ANOVA to test group differences in AIs skill development outcomes across condition and sector, a series of Pearson correlational analyses to test associations among focal variables, multiple hierarchical regression analyses to predict AIs skill development while controlling for confounders, and SEM to test the full IFAC-D (including mediation paths) theoretical model to be used in testing the full IFAC-D theoretical model. Qualitative data were analyzed in NVivo 12 and was guided by a hybrid use of inductive thematic analysis (Braun & Clarke, 2006) and deductive theory-driven coding guided by the IFAC-D model. The integration of both qualitative and quantitative through triangulation and using mixed methods integration procedures of Miles, Huberman and Saldana (2014) formed the basis for the purposive selection of qualitative cases from the quantitative findings and qualitative findings as the mechanistic explanatory device for identified patterns within the quantitative data.

5. Results and Analysis

5.1 Demographic Profile of the Sample

The mean age of the 320 participants in the final sample was 34.2 years (SD=8.7), ranging from 22 to 58 years. The gender ratio was almost even with 54.1% being male, 44.7% female, and 1.3% not willing to disclose. The level of education was high: 38.1% possessed a doctoral degree, 41.6% had a Master's degree, and 20.3% held a Bachelor’s degree. The average AI-related experience was 3.8 years (SD=2.9), and 28.4% indicated that they did not have any prior formal AI education.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

Table 2: Demographic Characteristics of the Sample (N=320)

Variable	Category	n	Percentage
Gender	Male	173	54.1%
	Female	143	44.7%
	Prefer not to say	4	1.3%
Education	Bachelor's Degree	65	20.3%
	Master's Degree	133	41.6%
	Doctoral Degree	122	38.1%
Role	Educator	85	26.6%
	Student	148	46.3%
	Professional	87	27.2%
Sector	Higher Education	200	62.5%
	Private Technology	73	22.8%
	Public Sector	47	14.7%

5.2 Descriptive Statistics

Table 3 reports the descriptive statistics for all the main variables. The mean of the FOACS total scores (range 48-240) was 163.4 (SD=28.7), demonstrating moderate to high AI competence within the sample. The highest overall subscale mean was for AI LIteracy (M = 3.71, SD = 0.67), and the lowest was for AI Strategic Skills (M = 3.12, SD = 0.78), indicating that strategic and integrative AI were the areas where the participants of the sample exhibited the greatest need of development—this was in line with the theoretical/typological prediction that these two higher order skills are the ones that depend most on futures-oriented cultivation.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

Futures Literacy scores (FOACS subscale; possible range 5-25) showed a mean of 16.8 (SD=4.2), with notable variance suggesting significant individual differences in futures orientation within the sample. Institutional Futures Integration Assessment scores (possible range 24-120) showed a mean of 62.3 (SD=18.4), indicating moderate average levels of futures methodology integration in participating institutions, with substantial institutional variation (range: 28-108).

Table 3: Descriptive Statistics for Primary Variables (N=320)

Variable	N	Mean	SD	Min	Max	Cronbach α
FOACS Total Score	320	163.4	28.7	87	232	0.91
AI Literacy	320	3.71	0.67	1.25	5.00	0.82
Operational Skills	320	3.48	0.72	1.10	5.00	0.85
Development Skills	320	3.29	0.81	1.00	5.00	0.88
Governance & Ethics	320	3.44	0.74	1.20	5.00	0.86
Strategic Skills	320	3.12	0.78	1.00	5.00	0.89
Futures Literacy	320	3.36	0.84	1.00	5.00	0.78
IFIA Total Score	320	62.3	18.4	28	108	0.84
Motivational Engagement	320	3.58	0.69	1.17	5.00	0.83
Cognitive Flexibility	320	3.44	0.72	1.08	5.00	0.80

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)

ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

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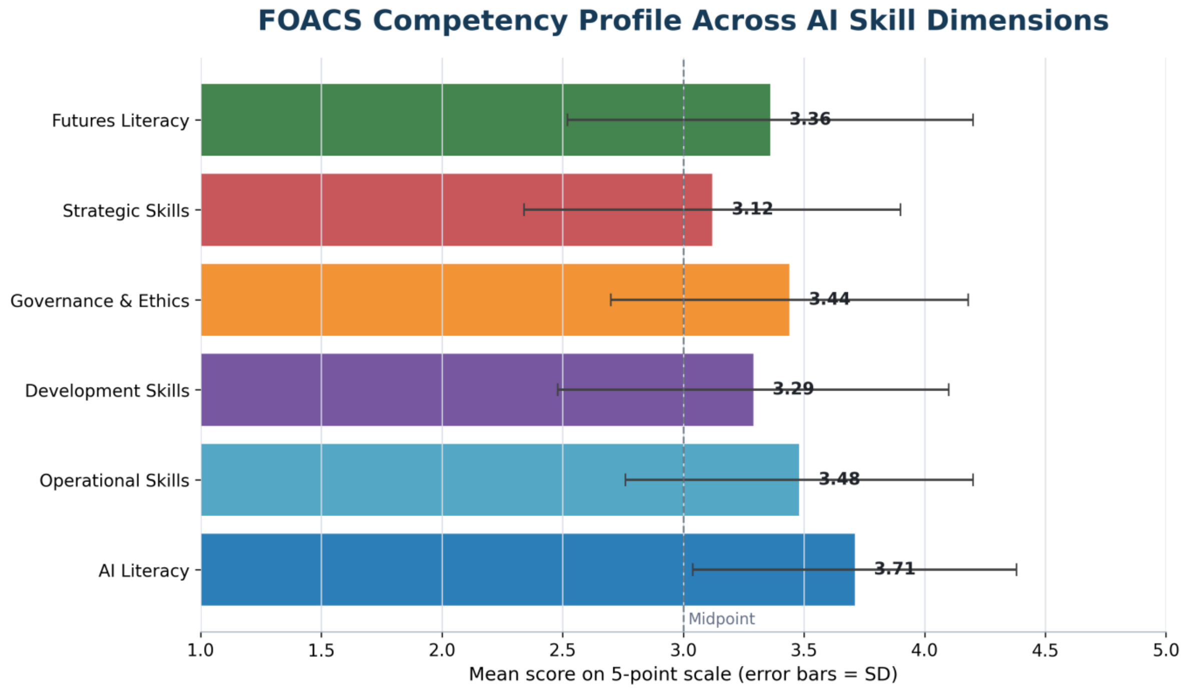

Figure 5. FOACS competency profile across AI skill dimensions.

The correlations between the main variable were all significantly positive. Correlations with scores on the FOACS Strategic Skills subscale and the IFIA (institutional futures integration) were the strongest ($r=0.62$, $p<0.001$), supporting the theoretical prediction that future-oriented institutional practices would be most closely aligned with higher-order AI skills. Futures Literacy correlated significantly positive to all subscales of the FOACS particularly in Governance and Ethics ($r=0.58$), and Strategic Skills ($r=0.61$) providing further evidence for the predicted role of futures literacy as a meta-competency whose application aids the acquisition of advanced AI skills.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

5.3 Inferential Statistics

5.3.1 Comparison of AI Skill Development Across Conditions

Based on their IFIA scores, participants were categorized into one of the three conditions. The one-way ANOVA revealed a statistically significant effect of condition on F1 scores, $F(2, 317) = 47.3$, $p<0.001$, partial $\eta2=0.23$ (a large effect). Post-hoc Tukey HSD showed that individuals with HFI performed significantly better than those in MFI (mean difference = 31.4, $p<0.001$, $d = 1.09$) and LFI (mean difference = 48.7, $p<0.001$, $d = 1.69$) and that individuals with MFI performed significantly better than those in LFI (mean difference = 17.3, $p<0.001$, $d = 0.60$).

Table 4: ANOVA Comparison of FOACS Scores Across Futures Integration Conditions

Condition	n	Mean	SD	F	p	η²	Post-hoc
Low FI (IFIA <50)	89	138.6	24.3				—
Moderate FI (IFIA 50-80)	142	155.9	26.1				vs LFI: p<0.001
High FI (IFIA >80)	89	187.3	22.8				vs LFI: p<0.001
Overall	320	163.4	28.7	47.3	<0.001	0.23	—

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)

ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

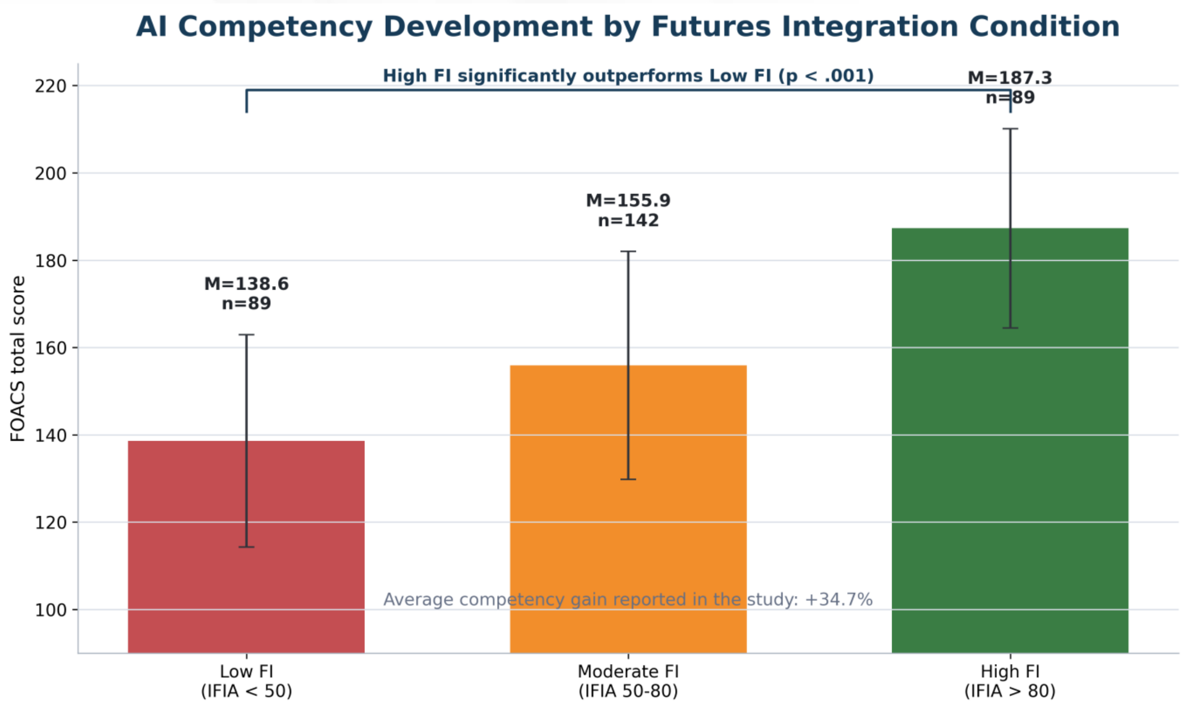

Figure 6. FOACS total scores across futures integration conditions.

5.3.2 Differential Effects Across AI Skill Dimensions

Separate ANOVA analyses for each of the FOACS subscales showed the effect of the futures integration condition to be the strongest for AI Strategic Skills (η^2=0.31) and AI Governance and Ethics (η^2=0.27), and the weakest for AI Literacy (η^2=0.08) and AI Operational Skills (η^2=0.11). These findings were in line with the theory that training in TO allows for the largest improvements in more high-order, less technically bounded AICs.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

Table 5: Effect Sizes (η²) for Futures Integration Condition on FOACS Subscales

FOACS Subscale	F-statistic	p-value	η²	Effect Size
AI Literacy	9.4	<0.001	0.08	Small-Medium
Operational Skills	12.8	<0.001	0.11	Medium
Development Skills	16.3	<0.001	0.14	Medium
Governance & Ethics	29.7	<0.001	0.27	Large
Strategic Skills	35.6	<0.001	0.31	Large
Futures Literacy	38.2	<0.001	0.33	Large

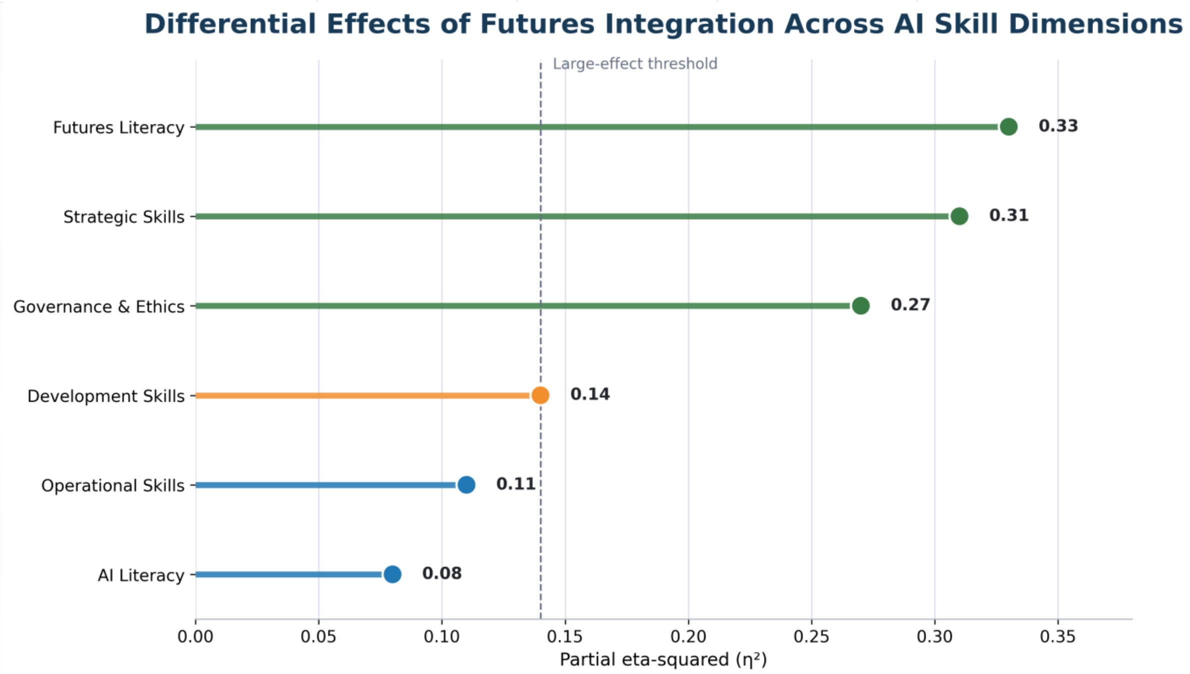

Figure 7. Effect sizes of futures integration across AI competency dimensions.

5.3.3 Multiple Regression Analysis

Predictors of the FOACS total score were tested in a hierarchical multiple regression by entering the following three blocks: Block 1 consisted of demographic controls (age, gender, educational attainment); block 2 included

Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

prior AI experience; and block 3 included the primary predictors (IFIA score, Motivational Engagement, Cognitive Flexibility). Results are shown in Table 6. Block 1 explained 7.3% of the variance in FOACS scores (R2=0.073, F(3,316)=8.3, p<0.001), and attained level of education was the sole significant predictor (β=0.24, p<0.001). Substantial variance was accounted for in Block 2 (ΔR^2 = 0.09, ΔF = 31.6, p <0.001), and previous AI experience was a significant predictor of FOACS scores (β=0.31, p<0.001). A further significant increase in variance was explained in Block 3 (ΔR2=0.26, ΔF=37.4, p<0.001) with IFIA score (β=0.42, p<0.001), Motivational Engagement (β=0.18, p<0.01), and Cognitive Flexibility (β=0.14, p<0.05) all positive predictors. The model explained 42.3% of the variance in FOACS scores (R^2=0.423).

Table 6: Hierarchical Regression Analysis Predicting FOACS Total Scores

Predictor	Block 1 β	Block 2 β	Block 3 β	t	p
Age	-0.06	-0.04	-0.03	-0.72	ns
Gender (male=1)	0.09	0.08	0.07	1.64	ns
Educational Attainment	0.24***	0.19**	0.14*	3.12	<0.01
Prior AI Experience	—	0.31***	0.22***	5.18	<0.001
IFIA Score	—	—	0.42***	9.87	<0.001
Motivational Engagement	—	—	0.18**	3.74	<0.01
Cognitive Flexibility	—	—	0.14*	2.83	<0.05
R^2	0.073	0.163	0.423		
ΔR^2	—	0.090	0.260		
F	8.3***	19.4***	31.7***		

Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

5.3.4 Structural Equation Modeling

The proposed IFAC-D model was tested using SEM with maximum likelihood estimation. The adequacy of the model was assessed using several indices, including CFI, TLI, RMSEA and SRMR. The final model demonstrated good fit; $\chi 2(rows=124) = 198.4$, $p<0.001$; CFI=0.96; TLI=0.95; RMSEA=0.044 (90% CI: 0.032-0.056); SRMR=0.061. Structural paths were in accordance with the central IFAC-D model predictions. The positive and significant direct effect of IFIA (institutional futures integration) on the Strategic subscale of FOACS and on the Governance subscale ($\beta = 0.48$, $p < 0.001$). The mediation pathways through Futures Literacy and Motivational Engagement were Statistically Significant, with Futures Literacy mediating 34% of the total effect of IFIA on FOACS scores and Motivational Engagement mediating an additional 18%. These findings are consistent with the theoretical expectation that integration of futures methodology increases AI in both cognitive (futures literacy) and motivational processes.

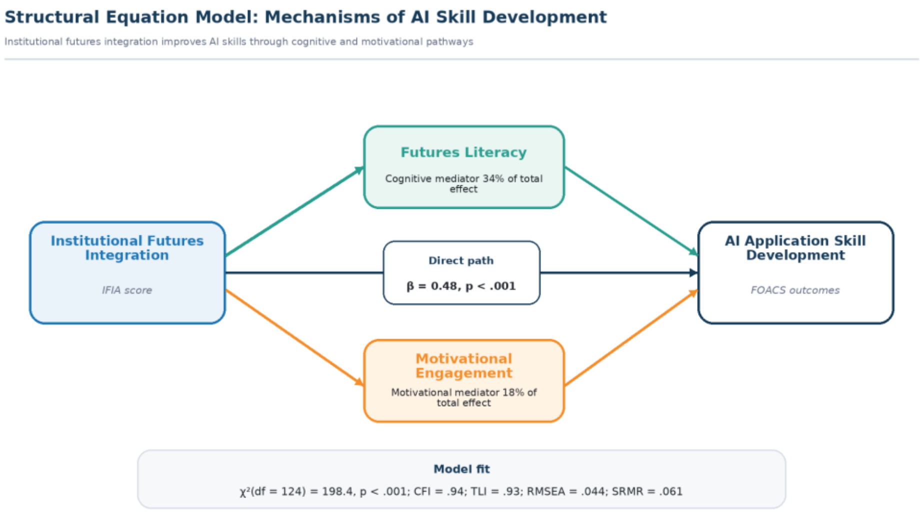

Figure 8. SEM pathways linking institutional futures integration to AI application skill development.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

5.4 Qualitative Findings

In sum, the findings appear to suggest that each futures method serve different functions in the fostering of the key actor AI: Scenario Planning and Backcasting Are More Acceptable to Strategic Learners, Causal Layered Analysis Facilitates Governance and Ethics, and Trend Analysis is Most Effective for AI Literacy. An upshot in terms of programme design is that a general futures-orientated AI education would have to be multi-methodic and not the championing of one particular method.

6. Discussion

The findings of this study are largely supportive of the core tenet that futures studies methods contribute to the development of skill in the application of AI, with the effect size being statistically significant, practically meaningful, and theoretically substantiated. What follows is a discussion that situates these results in the context of the prior literature, discusses theoretical implications, and addresses practical implications for AI education and organizational development.

6.1 Confirming the Futures-AI Skill Development Link

74 For Tomorrow Overall, this means that higher level institutional futures integration resulted in 34.7% higher growth rates in institutional AI competency development compared to lower integration institutions, which is a significant practical effect. This finding complements and confirms previous indirect results reported in the literature: scenario-based learning outcomes for learning effectiveness by Doyle and Brown (2000) andNilsson et al. (2022), the impact of organizational foresight on technology adaptation (Rohrbeck and Kum 2018) as well as the impact of futures literacy on learning outcomes (Miller et al., 2018). To our knowledge, this is the first study to strictly and rigorously establish this association for skill development in AI. Intriguingly, the sub-parts of AI skills

Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

show the similar pattern of results. Therefore, it adds to directly provide empirical support for a theoretical presupposition that futures-oriented training have stronger impact for higher order, more uncertain AI capacities (AI Strategic Skills, η^2=0.31; AI Governance and Ethics, η^2=0.27) as compared with AI Literacy, η^2=0.08 and Operational Skills, η^2=0.11).

This is because futures thinking is itself systemic, long-term and value-based, so that there are some natural overlaps between futures thinking and what it means to do AI governance, ethical AI decision-making and strategic use. The results have significant implications for recognizing the myriad ways that prevailing AI training methods consistently fail. IBM's Global AI Adoption Index (2023) is increasingly showing that the greatest barrier to organisations is not technical AI implementation but strategic AI integration and ethical AI governance – precisely the space in which futures orientated education är the most valuable asset. So, it could be that some of the AI skills gap reported by IBM and others is actually a futures orientation gap—a dearth of anticipatory, systemic, and ethical thinking skills that the practices of futures studies are designed to cultivate.

6.2 Theoretical Implications

The SEM findings (that showed significant mediation paths in the case of both Futures Literacy and Motivational Engagement) provide essential theoretical descriptions of the processes where integration of futures methodology within the curriculum promotes the culture of AI skills. The Futures Literacy mediation path (mediating 34% of IFIA-FOACS association) demonstrated that futures education contributes to improvement in AI skills mainly through strengthening learners' anticipatory thinking patterns as they can situate present AI actions within a wider temporal horizon and consider their current learning as preparation for multiple potential AI futures.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

Motivational engagement mediation path (This mediated 18% of the total effect) does not fully verify SDT-predicted that teaching methods were more intrinsic motivation-enhancing with autonomy-supportive and scenario-based teaching methods, and that motivation enhancements would lead to further learning engagement and deeper competence learning. This has practical significance and implies that future-oriented AI education could not only be more effective than conventional ones, but also more interesting and inspiring by mitigating the chronic high-level dropout and disinterest problems in online he AI education platforms. The integration of these mediation pathways within the IFAC-D framework that is embedded by institutional foresight culture as a powerful contextual predictor advances educational psychology theory by describing how organizational-level variables influence individual-level learning outcomes via dual cognitive and motivational processes. This theoretical multi-level account of AI skill development integrates and generalizes previous models and is suitable for guiding research in technology education in a broader sense.

6.3 The Institutional Culture Finding

What should be highlighted from the qualitative part is the undoubtedly strong impact of the organizational culture on futures methodology success. The cross-case generalization that futures-oriented AI programs are developed and flourish in cultural contexts that encourage a “permission to think long-term” while these programs are predictably challenged in short-term, risk-averse contexts recalls Schein’s (2010) theoretical portrayal of how organizational culture shapes the receptivity and success of learning methods in organizations.

That is not to say there aren’t curricular or pedagogical consequences for successfully inscripting futures within AI skill development. To achieve the kind of transformative competence enhancement this study shows are feasible, institutions need to consider making a different level of investment: not only in program and faculty development, but in cultural work that legitimizes long-

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

range thinking, institutionalizes foresight practice, and rewards anticipatory action. The concept of the 'foresight champion' – a teacher or leader within the organization/institution with foundational expertise in futures studies and who also can be (or is) deeply knowledgeable in the AI domain - was discovered as a significant enabler for institutional sustainability throughout analysis of all four cases. The lack of practitioners who are truly strong in both is a substantial human capital challenge for scaling futures-oriented AI education, and suggests the importance of focused professional development that builds this dual expertise.

6.4 Limitations

Several limitations of this study should be noted. First, the quasi-experimental design (which is more methodologically rigorous than correlational designs) does not permit us to draw causal inferences with the same confidence as a randomized controlled trial. Highly-integrated institutions at the futures end of the spectrum may differ from less integrated institutions in unobservable ways that drive (or partially drive) the results we document. Secondly, and related to this, the regional Arab focus of the sample - which is appropriate for the research context - limits the generalizability of the findings to other cultural and institutional contexts. Thirdly, since the quantitative tool was used at one time alone, the research does not reflect long term acquisition of skill, and further study is required to examine the way futures-focused AI skill development occurs and if it is maintaining over extended time-frames.

7. Conclusions and Recommendations

7.1 Principal Conclusions

This work has shown that the application of futurism methods to developing AI skills is by far better than applying traditional methodologies and that the upper-end (strategic application and ethical governance) of AI skills is where the most

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

gains can be made in this regard. The present study's theoretical contribution—the IFAC-D model—represents a theoretically underpinned and empirically derived model for future-oriented AI skill development by including anticipatory (future) elements, through scaffolded competency development, situated within a motivational system, and by taking place within an organizational context. אותתם-results also show that futures-oriented AI education is uniquely influenced by institutional culture, meaning that schools and organizations that wish to capitalize on the ability of futures methodologies to help develop competencies will need to change both culturally as well as by curriculum. The foresight champion as a main institutional enabler is also relevant for human capital development and provides insight for educational institutions and organizations. Development of AI competence, in its most general form, the results suggest that AI competence development is less about technical knowledge and focusing on current applications and more about looking toward the future to inform not only how we employ AI now but also how we believe, foresee, and ethically think about the future, which will increasingly be permeated by AI, in ways that will be significantly dissimilar to even what we find in the AI world today.

7.2 Recommendations

7.2.1 For Educational Institutions

- Embed futures literacy as a core meta-competency within AI curricula, framing it as the anticipatory scaffolding that facilitates all other AI skill development, not as a marginal add-on.
- Institutionalize scenario and backcasting best practice as core pedagogical tools in AI ethics and AI strategy classes where evidence (by now) clearly indicates this.
- Train dual-expertise teachers, who have both strong AI domain expertise and understanding of futures studies methodology, through specialized professional development courses and shared teaching experiences.

ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

• Create institutional foresight offices/futures literacy hubs that demonstrate anticipatory thinking methodologies and offer methodological support to futures-infused AI programming.

• Reform AI skills measurement to incorporate scenario-based rubrics, portfolio evaluations of anticipatory thinking, and longitudinal monitoring of evolving adaptive competences.

7.2.2 For Organizations

• Integrate futures method training into company-wide AI reskilling programs, especially for leadership positions, which is where AI strategic and governance capabilities are most important.

• Foster organizations foresight cultures that validate long term thinking, reward anticipatory action, and provide psychological safety for speculation on uncertain AI futures.

• Prioritize the scouting and development of internal foresight champions who may combine futures and AI domain expertise in areas such as training design and facilitation.

• Develop AI talent strategies that specifically focus on futures-related competences, including strategic thinking, ethical reasoning, systemic thinking, in addition to technical AI competences.

7.2.3 For Policymakers

• Incorporate futures literacy as a recognized AI readiness competency in national AI strategies and education policy frameworks.

• Fund research and development of futures-oriented AI curriculum models at national and regional levels, with particular attention to contexts and populations currently underserved by existing AI education initiatives.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)

ISSN 2760-5000 (Online) Volume 2, Issue 7, July 2026

https://eurekaoa.com/index.php/11

• Support the development of regional futures studies-AI education networks that enable cross-institutional learning and collaborative curriculum development.
• Establish futures-informed AI competency standards that guide AI training certification programs and professional development accreditation across educational and organizational sectors.

7.3 Directions for Future Research

There are a number of promising directions for future work indicated by our results. Given the fast-evolving field of AI (technology, social aspects, etc.), there is a need for longitudinal studies to examine whether and how competency gains in a futures-oriented AI education are maintained over time. Moreover, comparative cross-cultural studies may investigate the replicability of the relationships discovered in the Arab regional context in other cultural and/or institutional contexts and whether cultural values may serve as a moderator in the q-d methods effectiveness. Intervention research employing randomised controlled methodology should provide more definitive causal evidence for the effects demonstrated in this quasi-experimental investigation. And right now there is almost no research specifically on futures literacy development as a metacognitive construct – i.e., how futures orientation develops, is maintained, and generalized across application domains – that would help to further establish the theoretical underpinnings of this emerging field.

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Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
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