I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 18138

The Formation of AI Capital in Higher Education: Enhancing Students' Academic Performance and Employment Rates

Nick Drydakis

SEPTEMBER 2025

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 18138

The Formation of AI Capital in Higher Education: Enhancing Students' Academic Performance and Employment Rates

Nick Drydakis
Anglia Ruskin University, University of Cambridge and IZA

SEPTEMBER 2025

Any opinions expressed in this paper are those of the author(s) and not those of IZA. Research published in this series may include views on policy, but IZA takes no institutional policy positions. The IZA research network is committed to the IZA Guiding Principles of Research Integrity.

The IZA Institute of Labor Economics is an independent economic research institute that conducts research in labor economics and offers evidence-based policy advice on labor market issues. Supported by the Deutsche Post Foundation, IZA runs the world's largest network of economists, whose research aims to provide answers to the global labor market challenges of our time. Our key objective is to build bridges between academic research, policymakers and society.

IZA Discussion Papers often represent preliminary work and are circulated to encourage discussion. Citation of such a paper should account for its provisional character. A revised version may be available directly from the author.

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

The Formation of AI Capital in Higher Education: Enhancing Students' Academic Performance and Employment Rates

The study evaluates the effectiveness of a 12-week AI module delivered to non-STEM university students in England, aimed at building students' AI Capital, encompassing AI-related knowledge, skills, and capabilities. An integral part of the process involved the development and validation of the AI Capital of Students scale, used to measure AI Capital before and after the educational intervention. The module was delivered on four occasions to final-year students between 2023 and 2024, with follow-up data collected on students' employment status. The findings indicate that AI learning enhances students' AI Capital across all three dimensions. Moreover, AI Capital is positively associated with academic performance in AI-related coursework. However, disparities persist. Although all demographic groups experienced progress, male students, White students, and those with stronger backgrounds in mathematics and empirical methods achieved higher levels of AI Capital and academic success. Furthermore, enhanced AI Capital is associated with higher employment rates six months after graduation. To provide a theoretical foundation for this pedagogical intervention, the study introduces and validates the AI Learning–Capital–Employment Transition model, which conceptualises the pathway from structured AI education to the development of AI Capital and, in turn, to improved employment outcomes. The model integrates pedagogical, empirical and equity-centred perspectives, offering a practical framework for curriculum design and digital inclusion. The study highlights the importance of targeted interventions, inclusive pedagogy, and the integration of AI across curricula, with support tailored to students' prior academic experience.

JEL Classification: I23, I21, J24, J21, O33, O15, I24, J15, J16

Keywords: Artificial Intelligence, AI literacy, AI Capital, university students, grades, academic performance, employment rates

Corresponding author:
Nick Drydakis
School of Economics, Finance and Law
Centre for Inclusive Societies and Economies
Faculty of Business and Law
Anglia Ruskin University
East Road, Cambridge
CB1 1PT
Great Britain

E-mail: nick.drydakis@aru.ac.uk

1. Introduction

The rapid adoption of AI has created an urgent need for AI literacy among university students (Kong et al., 2023; Hornberger et al., 2023; Russell and Norvig, 2022). Educators and policymakers recognise that higher education shou ld equip students with AI literacy to keep pace with technological advancements in their professions and societies (Biagini, 2025; Bewersdorff et al., 2025; Chiu et al., 2024; Wang et al., 2023; Kong et al., 2023; Hornberger et al., 2023; Russell and Norvig, 2022; Long and Magerko, 2020). AI generates value across nearly all aspects of the workplace value chain, making it essential for graduates to acquire AI knowledge in order to meet contemporary demands and enhance their employment prospects (Drydakis, 2024a). As AI technologies enable a range of applications in the workplace, including the automation of routine tasks, advanced analytics, data-driven decision-making, and customer personalization, students require a solid foundation in AI to remain relevant in the evolving business landscape (Bewersdorff et al., 2025; Laupichler et al., 2022).

Research highlights that young professionals with AI training gain a distinct competitive advantage (Biagini, 2025; Hornberger et al., 2023; Kong et al., 2023). Indeed, Drydakis (2024a) defined AI Capital as a combination of AI-related knowledge, skills, and capabilities, and showed that graduates who developed this capital received significantly more job interview invitations, often for higher-paying roles, compared to those without it. The study underscored that possessing AI Capital enhances a graduate's employability. This finding suggests that employers value AI-literate candidates, as they can leverage technology to drive productivity and innovation.

Only recently have scholars begun to develop tools for measuring AI literacy among students (Biagini, 2025; Chiu et al., 2024; Kong et al., 2023; Carolus et al., 2023; Hornberger et al., 2023; Laupichler et al., 2022; Kong et al., 2021). However, despite the growing importance of AI literacy, there remains a notable lack of educational interventions aimed at evaluating how such knowledge can be developed within university settings for non-STEM students. This study seeks to address this gap.

The objectives of this study are guided by six key research questions. Firstly, what are the main dimensions of students' AI Capital? Secondly, how can AI Capital among university students be effectively measured? Thirdly, can AI education enhance students' AI Capital? Fourthly, what is the relationship between students' AI Capital and their academic performance in AI-related modules? Fifthly, how do demographic and academic factors influence variations in students' AI Capital? Sixthly, how is students' AI Capital associated with their employment outcomes?

To achieve these objectives, the study develops and validates the AI Capital of Students scale, a structured measurement tool designed to assess non-STEM university students' AI-related knowledge, skills, and capabilities within business contexts in England, UK. Grounded in the AI Capital framework (Drydakis, 2024a) and following DeVellis's (2003) eight-step framework for scale development, the study seeks to ensure the scale's reliability and validity by decomposing AI Capital into distinct components.

Beyond scale development, the study evaluates the impact of AI education through a 12-week AI-focused business module titled AI in Business Environments, delivered four times between 2023 and 2024, by assessing the development of students' AI Capital before and after the training. It also explores the relationship between AI Capital and academic performance, examining whether higher levels of AI Capital are associated with improved coursework outcomes. Importantly, the study investigates demographic and academic factors that may influence AI Capital, with particular attention to gender, race, and prior academic achievement. In addition, the study examines whether AI Capital is associated with students' employment outcomes six months after graduation.

This study contributes to the literature by advancing the AI Capital framework (Drydakis, 2024a), which helps to conceptualise its key dimensions. By introducing the AI Capital of Students scale, the study provides a structured assessment tool that both captures and extends the AI Capital framework as a multidimensional construct. The scale consists of three core elements: (1) knowledge, which includes an understanding of AI fundamentals and ethical considerations; (2) skills, which incorporate hands-on experience with AI tools, programming, and model development; and (3) capabilities, which reflect the strategic integration of AI in business contexts. This tripartite approach aligns with contemporary educational models that emphasise not only cognitive understanding but also the ability to apply and adapt knowledge in real-world scenarios (Biagini, 2025; Laupichler et al., 2022; Kong et al., 2021). By dissecting AI Capital into these distinct components, educators and policymakers can design targeted interventions that foster holistic proficiency in AI, better preparing individuals to navigate and contribute to an AI-infused society. The development and validation of the AI Capital of Students scale ensure that AI Capital can be systematically measured and tracked across different student cohorts. This contribution is particularly valuable for educators and policymakers seeking to evaluate the effectiveness of AI-related training programmes and curriculum interventions.

The study also contributes by empirically examining the role of AI educational interventions in supporting the development of AI Capital. Limited empirical evidence exists on whether such interventions can lead to measurable improvements in AI knowledge, skills, and capabilities (Bewersdorff et al., 2025; Hornberger et al., 2023; Kong et al., 2023; Long and Magerko, 2020). This study presents the learning intervention, its objectives, the corresponding skills addressed each week, and the improvement in AI Capital observed before and after the intervention. These improvements are evident across all three dimensions of AI Capital. The findings highlight the need for a balanced AI education strategy that integrates theoretical learning with practical application, ensuring that students develop both technical expertise and strategic thinking abilities. Furthermore, the study offers insights for academics and policymakers in shaping curricula and informing policy development.

Additionally, this study contributes to the evaluation of the relationship between AI Capital and academic performance, assessing whether students with higher levels of AI Capital achieve better

academic outcomes. The relationship between AI knowledge and academic performance remains significantly underexplored (Drydakis, 2024a). The study's design enables the measurement of students' actual academic performance in AI modules, as well as the role of AI Capital in shaping these outcomes. In doing so, it assesses not perceived AI literacy, but the actual relationship between AI Capital and academic achievement. The findings of the present study indicate that students who develop higher levels of AI Capital tend to achieve better grades in AI-related assignments. This contribution underscores the importance of integrating AI Capital into university curricula.

The study further contributes by assessing the role of demographic factors and prior academic performance in shaping both AI Capital and academic success. Existing literature suggests that students' backgrounds influence their engagement with AI, but few studies have empirically examined how these differences manifest in the development of AI literacy and academic performance (Bewersdorff et al., 2025; Chai et al., 2024; Hornberger et al., 2023; Kong et al., 2023; Kong et al., 2022). The present study finds that male students and those from White ethnic backgrounds tend to achieve higher AI Capital scores and better grades in AI-related modules than their female and non-White peers. Similarly, students with stronger backgrounds in core subjects such as mathematics and empirical methods tend to perform better in both AI Capital development and academic outcomes. While AI training significantly enhances AI capital across all demographic groups in the sample, disparities persist, underscoring the need for targeted interventions to help reduce learning divides. These findings highlight the importance of inclusive and equity-driven AI training strategies.

A unique contribution of this study lies in its design, which enables the observation of leavers' (i.e. graduates') employment outcomes six months after graduation, and the evaluation of whether their AI Capital is associated with their employment rates. This contribution is significant, as evidence linking students' AI Capital to graduation employment outcomes is largely absent from the literature. By tracking leavers' employment and evaluating the role of AI Capital, the study addresses a critical gap and underscores the real-world value of AI education in enhancing graduate employability. The study finds that AI Capital among non-STEM students is associated with higher employment, supporting the important role of AI education.

Finally, the study introduces and validates the AI Learning–Capital–Employment Transition model, which offers a pedagogically grounded and empirically supported framework for linking curriculum design, capability development, and graduate employability. The model captures how constructivist, experiential, and inclusive pedagogical strategies support the development of AI Capital and translate into improved academic and employment outcomes. By recognising structural inequalities, the need for inclusive instruction, and equity-centred design, the model provides a practical framework for aligning AI education with labour market demands and social responsibility. This contribution moves

beyond the identification of outcomes to offer a transferable and scalable model for universities seeking to embed AI literacy within inclusive and future-oriented curricula.

The remainder of the study is structured as follows. Section 2 presents the conceptual framework. Section 3 details the development of the AI Capital of Students scale. Section 4 describes the learning intervention and outlines the AI-related module. Section 5 presents the data set and data collection process. Section 6 reports the validation of the scale. Section 7 provides descriptive statistics. Section 8 presents the multivariate findings. Section 9 discusses the results, and Section 10 concludes the study.

2. Conceptual framework

2.1 Section Overview

This study examines the growing importance of AI literacy within higher education and introduces the AI Capital framework as a means of understanding AI-related knowledge, skills, and capabilities as a form of capital with academic, economic, and ethical significance. The section outlines the rationale for rethinking AI literacy as a multidimensional and strategic resource that links educational experiences to employment outcomes.

Section 2.2 presents the conceptual foundation for AI Capital. It explains how AI literacy extends beyond technical knowledge to include ethical reasoning and critical awareness, and how the AI Capital framework reframes these elements as assets with value in academic and labour market contexts. Drawing on human capital theory, signalling theory, and the capabilities approach, this conceptual framework provides a theoretical basis for understanding AI education as a pathway to learning and employability.

Then, Section 2.3 explores the academic impact of AI education. It reviews empirical evidence that demonstrates how AI-focused learning enhances cognitive abilities, such as problem-solving, analytical thinking, and data literacy. These skills are transferable across disciplines and positively influence academic achievement and student engagement, particularly when delivered through project-based and collaborative learning methods.

Section 2.4 highlights inequalities in access to AI education. It examines how demographic characteristics and institutional factors influence students' ability to engage with and benefit from AI learning. These disparities, which include differences by gender, ethnicity, socioeconomic status, and prior educational background, can restrict the development of AI Capital and reinforce broader structural inequities in higher education and employment.

Finally, Section 2.5 introduces the AI Learning–Capital–Employment Transition model. This model synthesises the conceptual, empirical, and structural insights presented in the previous sections by theorising the pathway from AI learning to the development of AI Capital, and then to higher

employment. It captures how inclusive AI education can support students from diverse backgrounds in building competencies that are increasingly valued in AI-integrated workplaces.

2.2 AI Capital: A Framework for Higher Education and Employability

AI literacy has rapidly become a core element of higher education, reflecting the increasing prevalence of AI in society, the labour market, and academic disciplines (Bewersdorff et al., 2025; Kong et al., 2023; Laupichler et al., 2022; Sollosy and McInerney, 2022; Russell and Norvig, 2022; Drydakis, 2022; Long and Magerko, 2020). Traditionally, AI literacy has been conceptualised as a multidimensional construct encompassing not only cognitive knowledge of AI systems, but also affective dimensions such as empowerment and digital confidence, as well as sociocultural dimensions, including ethical awareness (Chiu et al., 2024; Wang et al., 2023; Kong et al., 2023). Within this framework, AI-literate students are those who understand how AI systems function, how they should be applied responsibly, and how to critically evaluate their societal implications (Kong et al., 2023; Laupichler et al., 2022). This includes AI sensing, which captures the capacity to reflect on, question, and navigate AI technologies in relation to their ethical, political, and societal implications (Chiu et al., 2024; Crawford, 2021).

While this conception provides a strong foundation for interdisciplinary AI education, the emergence of the AI Capital framework (Drydakis, 2024a) marks a significant theoretical progression. AI Capital builds upon the multidimensional nature of AI literacy but extends it by framing AI-related knowledge, skills, and capabilities as forms of capital, akin to human capital, that possess economic, social, and signalling value in the labour market (Ignatow and Robinson, 2017; Hodgson, 2014; Sen, 1997; Bourdieu, 1983). In doing so, it repositions AI literacy from a general educational outcome to a strategic asset that enhances academic performance, employability, employment outcomes, competitiveness, and innovation (Drydakis, 2025a). AI Capital is not limited to economic advancement; it also enables students to evaluate when and why AI should be applied, to question potentially unjust deployments of AI systems, and to participate in shaping socially responsible innovation. This reconceptualisation is particularly relevant in an era where AI integration is rapidly transforming labour market demands. As employers increasingly seek digitally fluent graduates capable of navigating AI-driven tools and environments, students equipped with higher levels of AI Capital are more likely to access high-quality employment opportunities, secure roles in emerging sectors, and adapt to technological changes in the workplace (Drydakis, 2025a; 2024a).

The AI Capital framework is underpinned by three main theoretical traditions. First, it draws on classical human capital theory (Becker, 1964), which posits that education and training increase individual productivity, employment prospects and earning potential. Acquiring AI knowledge, skills, and capabilities is therefore viewed as an investment in human capital, yielding returns through enhanced problem-solving ability and workplace relevance. Second, signalling theory (Spence, 1973) is central to

the AI Capital framework. It suggests that AI knowledge, skills, and capabilities can serve as credible signals to employers that individuals are technologically agile and well-prepared for digitally transformed environments. Drydakis (2024a) supports this with evidence from England, demonstrating that job applicants signalling AI Capital gained greater access to higher-paid occupations compared to those without such indicators. Third, the framework draws on the capabilities approach (Sen, 1997), which emphasises not only what students know about AI, but also what they are able to do with that knowledge. Capabilities, in this context, refer to the practical and strategic application of AI tools in real-world scenarios, such as interpreting AI-generated analytics, aligning machine learning outputs with organisational strategy, or evaluating the ethical implications of deploying AI systems. It also includes the freedom to reject the use of AI in contexts where it may perpetuate bias, violate norms of fairness, or generate social harm. From this perspective, AI Capital not only supports productivity and performance but also nurtures ethical reasoning and digital responsibility (Crawford, 2021; Noble, 2018).

AI Capital elevates AI literacy by moving beyond basic awareness and comprehension to encompass economic value, strategic application, and labour market signalling. It integrates empowerment, ethical reasoning, and cognitive understanding, embedding these within a framework that explicitly links educational attainment to both academic performance and workplace success (Drydakis, 2024a). AI Capital reframes AI literacy not merely as a personal accomplishment but as a form of competitive advantage, with implications for learning outcomes, academic progression, and employment payoffs. It places emphasis on functional fluency with AI and the ability to use it both effectively and ethically in decision-making contexts. From this perspective, effective AI Capital involves not only understanding how AI works, i.e., how algorithms operate, but also why and when to deploy it. It further requires learners to understand the societal consequences of algorithmic systems and to reflect critically on AI's role in reinforcing or challenging inequality or marginalisation (Crawford, 2021; Noble, 2018). This reconceptualisation is particularly relevant in non-STEM fields, where graduates are increasingly expected to interpret AI-generated insights and integrate them into both operational and strategic planning.

Empirical studies offer support for the AI Capital framework. Research conducted in Europe, Asia, and America by Biagini (2025), Drydakis (2024a; 2025a), Bewersdorff et al. (2025), Hornberger et al. (2023), Wang et al. (2023), Kong et al. (2023), and Chai et al. (2024) demonstrates that AI literacy and AI knowledge, skills, and capabilities, as well as relevant AI-related educational interventions, enhance students' digital self-efficacy, digital capabilities, ethical awareness, confidence in using AI technologies, academic performance, and employability. Notably, these improvements are not confined to STEM students. Interventions such as concept-based AI courses offered in non-computer science disciplines have been shown to benefit students across the humanities, health, education, and business. This suggests that the strategic dimension of AI Capital can be cultivated even in the absence of prior technical

knowledge (Drydakis, 2024a; Kong et al., 2023; Kong et al., 2022). Students engage with AI tools without needing to write code, illustrating that AI knowledge can be developed in conceptually rich yet technically inclusive environments (Hornberger et al., 2023; Kong et al., 2023; Kong et al., 2022). Moreover, these programmes typically incorporate project-based learning, ethical reasoning, and collaborative problem-solving, all of which contribute to the development of AI skills and capabilities, a key component of AI Capital. Critically, such approaches also support the cultivation of AI sense, enabling students to explore the wider social, ethical, and environmental impacts of AI systems and to engage with AI technologies not only as users but also as critical thinkers (Drydakis, 2024a).

2.3 The Academic Impact of AI Education

AI education has been shown to enhance both students' theoretical understanding of AI and their practical capabilities, which are essential for success in AI-integrated coursework and academic performance (Drydakis, 2024a). One of the primary mechanisms through which AI education improves academic performance is by strengthening students' digital problem-solving and data literacy skills, which are transferable across disciplines. Concept-based AI modules and training programmes often expose students to structured thinking, analytical modelling, and evidence-based decision-making. These cognitive skills enhance academic tasks such as data interpretation, critical reading, and research design (Singh et al., 2025; Hornberger et al., 2023). For example, students who learn to interpret algorithmic outputs in AI courses often demonstrate improved ability to analyse complex datasets and make justified inferences in coursework assessments, particularly in fields such as business, health, and social sciences (Kong et al., 2023).

Furthermore, AI education frequently includes project-based learning and collaborative assignments, which support cognitive development. When students work in teams to solve real-world problems using AI tools, such as chatbots, data visualisation software, or automated decision systems, they not only acquire technical fluency but also develop higher-order academic skills. These include argument construction, hypothesis testing, and the synthesis of interdisciplinary knowledge (Chai et al., 2024; Drydakis, 2024a). Such pedagogical approaches are associated with improved academic engagement and persistence, especially among students without prior technical training.

In addition, AI education helps students become more strategic and autonomous learners by fostering self-efficacy in navigating digital systems and academic tools. Studies have shown that students who gain confidence in using AI applications, including natural language processing for essay drafting or predictive tools for simulation tasks, are more likely to take initiative in their learning, use formative feedback effectively, and engage in self-directed exploration of topics (Zahid et al., 2025; Singh et al., 2025). These behaviours are positively associated with academic performance across a wide range of

disciplines, suggesting that AI education has a broad enabling effect on academic outcomes, not limited to technical or computing domains.

Empirical evidence establishes significant positive relationships between AI literacy, AI usage, AI learning outcomes, and academic performance (Singh et al., 2025). Specifically, students with higher levels of AI literacy are more likely to engage actively with AI technologies and tools for educational purposes, leading to improved learning experiences and academic achievement (Singh et al., 2025). Moreover, AI literacy plays a pivotal role in fostering critical cognitive skills such as problem-solving and analytical thinking, which are increasingly important in contemporary higher education (Singh et al., 2025). Attitudinal factors also appear to influence these outcomes, with a positive attitude towards AI being significantly associated with higher levels of AI literacy and academic success (Zahid et al., 2025).

2.4 Inequalities in Access to AI Education and Capital Formation

It is essential to recognise that the development of AI Capital may not occur in a vacuum. Demographic characteristics and prior educational performance often interact to influence students' ability to accumulate AI-related knowledge, skills, and capabilities (Bewersdorff et al., 2025; Hornberger et al., 2023). These factors can act as either constraints or enablers, shaping the extent to which students engage with and benefit from AI education. Demographic characteristics, including gender, ethnicity, and socioeconomic status, are consistently associated with disparities in engagement with AI and other STEM-related fields. A growing body of literature highlights that male students and those from White and higher-income backgrounds are more likely to report greater self-confidence and interest in technology-intensive subjects (Bewersdorff et al., 2025; Cachero et al., 2025).

Bewersdorff et al. (2025), drawing on a survey of 1,465 university students across the United States, the United Kingdom and Germany, found that students with more frequent AI usage and more positive attitudes towards AI, often associated with higher socio-economic status and digital access, were more likely to develop strong AI self-efficacy. The study identified alternative student profiles that varied in their engagement, suggesting that educators need to tailor interventions based on students' attitudinal and behavioural orientations. Similarly, Cachero et al. (2025), in an observational study conducted in Spain among undergraduate students, reported significant gender disparities in AI-related self-perceptions. Female students consistently underreported their perceived knowledge of AI, their ability to apply AI tools, and their support for AI development, despite equivalent levels of enrolment and disciplinary participation. This may stem from earlier exposure to digital tools, encouragement from teachers or parents, and stronger representation within curricular content. In contrast, students from historically underrepresented groups often face implicit biases, stereotype threat, and a lack of relatable role models in AI-related fields (Intahchomphoo and Gundersen, 2020).

In their systematic review of AI and race, Intahchomphoo and Gundersen (2020) underscore how structural inequalities shape access to AI knowledge and reinforce racialised patterns in the development and application of AI tools. These dynamics can hinder engagement and academic performance, potentially reinforcing a cycle in which the most confident or well-prepared students continue to benefit from AI education, while others are left behind, even in the presence of structural interventions (Intahchomphoo and Gundersen, 2020). Although these findings are primarily based on studies in Europe, North America, and South Asia, they offer valuable insights into the interaction of demographic variables with AI confidence and learning outcomes.

Modules that involve machine learning, data modelling, or algorithmic decision-making often assume a foundational level of quantitative knowledge (Bewersdorff et al., 2025; Biagini, 2025; Chai et al., 2024; Hornberger et al., 2023). Students with strong prior knowledge in these areas are more likely to thrive and gain confidence when working with AI tools (Zahid et al., 2025; Singh et al., 2025). Conversely, those from non-quantitative disciplines or with gaps in basic skills may struggle to keep pace, even if they are motivated to learn. This challenge is not only cognitive but also psychological: a negative attitude towards AI and weaker academic preparation are often linked to lower self-efficacy, which can adversely affect learning outcomes and persistence in technically demanding subjects (Zahid et al., 2025; Singh et al., 2025). As a result, students with limited exposure to digital technologies or weak foundational knowledge may find AI education intimidating or inaccessible, restricting their ability to develop AI Capital.

Institutional disparities further compound these inequities. Variations in access to qualified instructors, state-of-the-art AI tools, and interdisciplinary course offerings can result in vastly unequal learning opportunities across universities or departments (Biagini, 2025; Chiu et al., 2024; Hornberger et al., 2023). Students attending well-resourced institutions are more likely to engage with up-to-date AI content and benefit from hands-on, applied learning experiences. In contrast, students in under-resourced settings may receive abstract or outdated instruction, with limited opportunities to apply AI in real-world business or policy contexts. Additionally, when AI modules are optional or positioned at the margins of the curriculum, students from certain academic tracks may never encounter them at all, further widening disparities in AI knowledge across disciplines (Drydakis, 2024a). The digital divide also manifests in students' attitudes towards AI. Some learners may express scepticism or hesitation due to limited familiarity with AI or concerns about its ethical implications (Cachero et al., 2025). Others, particularly women and students from marginalised backgrounds, may experience stereotype threat or a lack of visible role models, further inhibiting their engagement (Cachero et al., 2025).

Given these intersecting challenges, there is a clear imperative for universities to offer AI educational interventions that are both inclusive and strategically designed (Drydakis, 2024a; Hornberger et al., 2023). For universities and policymakers, this reinforces the need to invest in inclusive AI

education across disciplines, ensuring that all students, regardless of background, have the opportunity to develop and signal their AI Capital. Integrating AI training into the core of university education directly responds to the growing demand from employers for graduates who can interpret AI-generated insights and contribute to data-informed decision-making (Drydakis, 2025a). More broadly, AI Capital should be understood as a framework for nurturing not only job readiness but also the ethical, reflexive, and civic capacities necessary to shape inclusive, fair, and accountable AI systems. Ultimately, the evidence underscores that universities have both an opportunity and a responsibility to shape students' AI Capital. AI Capital should therefore be understood not only as an educational outcome, but as a strategic employability asset. Equally, it represents a foundation for ethical awareness, critical thought, and socially responsible engagement with digital technologies in a rapidly evolving world.

2.5 The AI Learning–Capital–Employment Transition Model

This section presents the AI Learning–Capital–Employment Transition model, which theorises the pathway from AI education to the development of AI Capital, and subsequently to increased employment outcomes. The model draws on conceptual foundations related to the definition of AI literacy, the educational impacts of AI training, and the structural challenges affecting access and engagement. Together, these insights establish a dynamic and inclusive framework that links curriculum design, learning processes, and labour market readiness.

At its core, the AI Learning–Capital–Employment Transition model positions structured AI learning, exemplified by university modules such as AI in Business Environments, as the starting point for the accumulation of AI Capital. Through engagement with AI tools, concepts, and real-world applications, students develop a composite set of competencies, including technical knowledge, critical understanding, ethical reasoning, and strategic application. These competencies form the foundation of AI Capital. The supporting theoretical traditions suggest that AI Capital not only improves educational outcomes but also serves as a credible signal of readiness for digitally transformed workplaces.

The evidence presented suggests that AI education enhances students' academic performance by strengthening digital problem-solving, data literacy, and analytical thinking. These cognitive skills are transferable across disciplines and contribute to deeper engagement, improved learning autonomy, and higher attainment. Project-based and collaborative pedagogies reinforce these effects, particularly for students from non-technical backgrounds. The model therefore conceptualises AI learning not merely as content delivery, but as a process of capability building that supports both academic success and future employability.

At the same time, the development of AI literacy is shaped by inequalities in access, prior knowledge, and institutional provision. Gender, ethnicity, socioeconomic status, and educational background all influence students' confidence with and exposure to AI. Structural barriers can constrain

students' ability to benefit from AI learning. Consequently, the AI Learning–Capital–Employment Transition model highlights that these contextual variables can significantly shape the transition from AI learning to the development of AI Capital and employment. It recognises that inclusive and well-resourced pedagogical approaches are necessary to ensure equitable AI Capital development across diverse student populations.

The AI Learning–Capital–Employment Transition model provides a synthesised framework for understanding how higher education can prepare students for AI-integrated work environments. It captures the process through which pedagogical engagement with AI leads to the development of AI Capital and, in turn, to enhanced employability. Moreover, the model underscores the importance of embedding inclusive design principles and structural supports to mitigate disparities in outcomes. AI Capital should be recognised not only as an academic outcome, but also as a strategic asset that equips students with the capabilities and ethical judgement required to navigate and shape the future of AI in society. This model highlights the need for universities to align curricula, pedagogy, and institutional policy in support of equitable and future-oriented AI education.

Figure 1 illustrates the AI Learning–Capital–Employment Transition model.

[Figure 1]

3. AI Capital of Students scale

Expanding upon the concept of AI Capital (Drydakis, 2024a), this study develops the AI Capital of Students scale to measure the level of AI Capital among university students (Echeberria, 2022; Agrawal et al., 2022; Munoz and Naqvi, 2018). The development of this scale follows DeVellis's (2003) eight-step framework for creating new measurement tools, ensuring its reliability and validity in assessing students' AI knowledge, skills, and capabilities in a business context.

The first step in this framework was to define the purpose of the AI Capital of Students scale. Informed by the AI Capital framework, the scale aims to measure the level of AI knowledge, skills, and capabilities among students studying economics with a business focus. Following this, the second step involved generating an initial item pool to effectively capture the scale's objectives. This was achieved through a literature review incorporating both theoretical and empirical studies on students' engagement with AI in business economics (Drydakis, 2024a; Kong et al., 2023; Wang et al., 2023; Carolus et al., 2023; Hornberger et al., 2023; Laupichler et al., 2022; Russell and Norvig, 2022; Kong et al., 2022; Echeberria, 2022; Agrawal et al., 2022; Drydakis, 2022; Kong et al., 2021; Munoz, and Naqvi, 2018). From this, a list of 58 items was developed to reflect the core dimensions of AI Capital.

The third step focused on determining the measurement format. Based on the literature, a five-point Likert scale was chosen to assess the extent to which university students agreed with each

statement, aligning with standard measurement practices in the social sciences (DeVellis, 2003). This format ensures standardisation, ease of interpretation, and the ability to capture variability in AI Capital.

The fourth step involved expert review and refinement of the scale. A panel of seven university AI business instructors, four AI business experts, and three IT and technology strategists reviewed the initial pool of 58 items for relevance, clarity, and representativeness. Based on their feedback, redundant, unclear, and overly technical items were either removed or refined to improve construct coverage. The revised scale comprised 40 refined items, ensuring it captured the full scope of AI Capital.

As shown in Appendix Table A.I, the Knowledge theme, comprising 21 items, measures students' understanding of AI fundamentals. It evaluates their familiarity with AI-driven decision-making processes, as well as considerations relating to data privacy and ethical challenges in AI adoption. A strong knowledge base enables students to recognise AI's potential to drive business and economic efficiency.

In addition, the Skills theme, consisting of seven items, assesses students' practical expertise in using AI tools. This includes the application of AI in data preparation and analysis, as well as business performance evaluation. Skills to apply AI in business operations are crucial for students to optimise decision-making and develop AI-based solutions tailored to real-world business needs.

Moreover, the Capabilities theme, which includes 12 items, examines students' ability to strategically leverage AI in business environments. This involves integrating AI into business and economic strategies and enhancing customer interactions. Additionally, this theme evaluates students' capacity to develop AI-driven business and economics solutions that create competitive advantages, drive innovation and support long-term business sustainability (Drydakis, 2025b; 2024b).

[Appendix, Table A.I]

The fifth step involved conducting a validity assessment through pilot testing with 20 university students. This was undertaken to evaluate the scale's face validity, content validity, construct validity, criterion validity, discriminant validity, and convergent validity (DeVellis, 2003). For instance, face validity was assessed by asking students whether the scale items appeared to measure AI knowledge in business settings in a clear and understandable manner. For example, students were asked whether the statement 'I understand the differences between AI, machine learning, deep learning, and automation' accurately reflected their AI-related knowledge. The results of the pilot study confirmed that the scale effectively captured the AI Capital themes and aligned with theoretical expectations.

In the sixth step, as outlined in the section 'Data set and data gathering', the scale was administered in 2023 and 2024 to a sample of 120 university students, both before and after the AI in Business Environments module, generating 240 observations. The seventh step involved evaluating item performance using exploratory factor analysis (DeVellis, 2003) to assess the scale's internal consistency and model fit. The results of this analysis are presented in the section 'Scale Validation'. Finally, the

eighth step focused on scale optimisation to ensure efficiency by testing alternative scale specifications. At this stage, the scale's consistency was assessed both as a complete 40-item scale and as a scale comprising the three identified themes: Knowledge, Skills, and Capabilities. The findings from this evaluation are also presented in the 'Validation of the AI Capital of Students scale' section.

4. Module structure

4.1 Students enrolled in the module

The AI in Business Environments module was designed for university students studying economics who had previously completed modules in mathematics, empirical methods (including statistics and econometrics), and economics (microeconomics and macroeconomics). A pass in these modules was a prerequisite for enrolment. The module was delivered to third-year students (i.e. those in their final year of study under the UK system) and had a capacity of 30 students per semester. Places were allocated on a first-come, first-served basis following an e-announcement sent via university email to students enrolled in the economics course. To ensure equitable access and minimise selection bias, neither students' degree averages nor their performance in core modules were considered as criteria for enrolment. Between 2023 and 2024, the module was delivered on four occasions, with 30 students enrolling in each iteration, resulting in a total sample of 120 students.

4.2 Aims of the module

The AI in Business Environments module aimed to develop students' knowledge, skills, and capabilities in AI concepts within business-economics contexts, ultimately fostering their AI Capital (Russell and Norvig, 2022; Echeberria, 2022; Agrawal et al., 2022; Munoz and Naqvi, 2018). The course sought to bridge the gap between AI theory and its application in business, with a focus on AI-driven insights, predictive analytics, process automation, and risk management. Its primary objective was to equip students with a robust understanding of AI methodologies and their application in business decision-making (Drydakis 2025b; 2024b).

The module adopted an interdisciplinary approach, integrating AI knowledge with practical coding experience and strategic thinking to prepare students for roles in data-driven business-economics environments (Russell and Norvig, 2022; Echeberria, 2022; Agrawal et al., 2022; Munoz and Naqvi, 2018). By the end of the course, students were expected to demonstrate knowledge of AI concepts, including machine learning, deep learning, automation, and big data applications. They were also expected to apply supervised and unsupervised learning techniques to develop AI models for business use cases. In addition, the module aimed to familiarise students with AI tools such as Python and R for predictive analytics and data-driven decision-making. It also sought to equip students with the knowledge required to address bias and ethical challenges in AI applications by implementing fairness constraints

and governance measures. Furthermore, the module aimed to develop students' ability to design AI-driven business-economics solutions and to effectively integrate AI into existing business operations. Another key objective was to enable students to identify opportunities for AI implementation across various business functions, including customer segmentation, risk assessment, and financial forecasting. Students were also trained to manage AI deployment by collaborating with cross-functional teams and evaluating implementation risks. This holistic approach ensured that students not only developed technical proficiency but also gained an appreciation of the broader implications of AI in business-economics environments.

As shown in Appendix Table A.II, each item in the AI Capital of Students scale (Panel I) corresponds to a specific learning objective (Panel II) and an applied learning development (Panel III). For example, the first item (IS1), 'I understand the differences between AI, machine learning, deep learning, and automation', aligns with the learning objective 'LO1: Understand the differences between AI, machine learning, deep learning, and automation' and the applied learning development 'ALD1: Development of concept differentiation, critical thinking, digital literacy, use of technical terminology, and understanding of AI categories'. This structured approach ensures that the AI in Business Environments module is aligned with clearly defined learning objectives and applied learning developments associated with the concept of AI Capital.

[Appendix, Table A.II]

4.3 Delivery of the module

The module was delivered over 12 weeks and comprised weekly four-hour lectures incorporating hands-on coding activities, along with three-hour seminar sessions held in computer laboratories. The lectures introduced foundational AI concepts, while the seminars facilitated the practical implementation of AI techniques using software. Students were required to bring their laptops to all lectures to participate in real-time coding exercises, ensuring active engagement with the material and the development of essential technical skills. The structure and content of the module were designed to shape students' AI Capital, encompassing the knowledge, skills, and capabilities required to understand, apply, and communicate AI-driven solutions in business-economics contexts. Through a progressive approach, the aim was for students to develop not only technical proficiency, but also the confidence and insight required to integrate AI responsibly and effectively into decision-making, innovation, and organisational strategy.

The delivery is grounded in academically validated and industry-relevant methodologies, with all tools and techniques, such as Python and R programming, classification and regression models, neural networks, reinforcement learning,cloud deployment, and fairness auditing, accurately reflecting current practice in AI and business analytics education (Russell and Norvig, 2022; Echeberria, 2022; Agrawal et

al., 2022; Munoz and Naqvi, 2018). Seminar activities were carefully aligned with theoretical content to ensure students engaged with real-world AI frameworks and tools such as TensorFlow, scikit-learn, and AWS. In addition, critical issues such as data ethics, governance, and model interpretability were embedded to reflect regulatory and societal expectations (Russell and Norvig, 2022; Echeberria, 2022; Agrawal et al., 2022; Munoz and Naqvi, 2018).

In the first three weeks, students were introduced to fundamental AI concepts, beginning with an overview of AI, machine learning, deep learning, and automation (LO1). In Week 1, the lectures examined AI's role in contemporary business–economic environments, with a focus on its practical applications and wider impact (LO29). Seminars introduced students to Python and R for AI applications, where they implemented basic AI models (LO24). Subsequently, in Week 2, the module delved deeper into core AI concepts such as model training, optimisation, and data representation (LO2). The importance of big data in AI applications was also highlighted, particularly the dimensions of volume, variety, and velocity (LO4). Seminars provided hands-on experience in preparing data, enabling students to explore datasets and identify emerging trends (LO22). In parallel, students examined privacy concerns related to AI data usage, including data protection and user consent, to better understand the ethical and security implications (LO18). Moreover, in Week 3, students investigated the differences between supervised and unsupervised learning, with a particular focus on real-world applications such as customer segmentation and credit scoring (LO3, LO34). Seminars supported this learning by guiding students through the implementation of classification models, such as decision trees, for customer segmentation tasks, and by assessing model performance using metrics including accuracy, and precision (LO25).

Weeks 4 to 6 focused on more advanced AI techniques. In Week 4, students explored predictive analytics methods, including forecasting and trend analysis (LO5). Natural language processing techniques, such as sentiment analysis, were also introduced (LO6). Seminars guided students in building regression models for sales forecasting and conducting sentiment analysis using natural language processing techniques (LO23). In Week 5, the focus shifted to neural networks, including convolutional and recurrent neural networks (LO8). The application of neural networks in finance and marketing was also examined (LO33). During seminars, students were introduced to TensorFlow and Keras, through which they implemented a basic neural network and performed time series forecasting using recurrent neural networks (LO10). Week 6 introduced reinforcement learning, covering Q-learning and policy gradient methods (LO7), alongside discussions on the role of cloud computing (e.g. AWS and Google Cloud) in AI model deployment (LO11). In seminars, students deployed AI models on cloud platforms (LO12). Additionally, students explored the challenges of overfitting and underfitting in AI models, implementing techniques such as cross-validation, L2 regularisation, and dropout layers to improve model generalisation (LO26).

In Week 7, students examined bias in AI models and datasets, addressing issues such as selection bias and algorithmic bias (LO13). Ethical considerations in AI, including data ethics and regulatory compliance, were also discussed (LO16, LO17). Seminars concentrated on detecting and mitigating bias in datasets, applying fairness constraints in AI models, and understanding how biased data can result in discrimination and inaccurate predictions (LO14, LO15). In Week 8, students explored data-driven decision-making in AI (LO9) and the role of human–AI interaction in promoting interpretability and trust (LO19, LO20). The seminar involved the application of explainable AI techniques to enhance the transparency of model outputs and support students in interpreting complex AI predictions. Week 9 addressed AI's role in business innovation and competitive advantage, highlighting how AI can drive process optimisation and improve customer service (LO31). The concept of leveraging AI for strategic advantage was also explored (LO32). In seminars, students applied AI techniques for customer segmentation and targeted marketing, testing models to optimise business performance. Additionally, they conducted scenario analysis using AI-supported simulations, such as A/B testing, where alternative strategies are compared, and sensitivity analysis, to evaluate different strategic options (LO27).

In Week 10, students examined the integration of AI into business processes (LO36) and were introduced to risk management strategies, including AI-related security, ethical concerns, and failure prevention (LO38, LO39). Seminars provided hands-on experience with implementing security measures in AI models and applying auditing techniques to ensure responsible deployment. Week 11 concentrated on AI project deployment strategies (LO28, LO35) and highlighted the importance of cross-functional collaboration in AI initiatives (LO40). A key focus involved evaluating the potential benefits and limitations of AI in business, such as cost reduction, risk mitigation, and accuracy enhancement, while ensuring that AI solutions aligned with strategic business objectives (LO30). In the final week (Week 12), students explored AI's role in emerging technologies, including the Internet of Things (IoT) and autonomous systems (LO21). Discussions on AI governance and future trends (LO37) enabled students to critically reflect on the evolving AI landscape and the implications for business and society. The seminar concluded with business cases designed to strengthen students' ability to develop, deploy, and explain AI solutions within real-world business contexts.

4.4 Module assignments

The assessment strategy for the AI in Business Environments module was designed to evaluate students' knowledge, analytical skills, and strategic thinking in applying AI within business–economics contexts. The module assignment consisted of two key components: an AI model development and business application report (50%), and an AI strategy and implementation proposal (50%). This assignment was structured to ensure that students demonstrated their ability to develop AI models,

analyse their impact on business–economics decision-making, and formulate strategic recommendations for AI integration in real-world business environments.

The first component, AI model development and business application report, required students to develop an AI-based model to address a specific business challenge and present their findings in a 2,000-word written report. Students were tasked with selecting a business case where AI could provide meaningful insights, such as customer segmentation, demand forecasting, or risk assessment. They were expected to prepare and clean a dataset (LO22), apply appropriate AI techniques, such as regression analysis, classification, clustering, or reinforcement learning, based on the nature of the selected business case (LO7, LO23, LO25), and evaluate their model's performance using suitable metrics (e.g. accuracy, precision, recall, or F1 score), as appropriate to the task (LO10, LO26).

The report required students to interpret AI-driven insights (LO9, LO29), discuss the ethical implications of AI applications (LO13, LO14, LO15, LO16), and propose strategies to enhance model transparency and fairness (LO20). These themes reflected the module's emphasis on ethical and responsible AI. This component assessed students' ability to translate AI concepts into practical business applications while critically reflecting on potential bias, fairness, and governance considerations (LO37).

The second component, AI strategy and implementation proposal, focused on business strategy and AI integration. This assessment required students to submit a 2,000-word report outlining a business function where AI could generate a competitive advantage (LO32) and to develop a comprehensive AI implementation plan. Their proposal needed to address AI deployment strategies (LO28), integration into existing business processes (LO36), and deployment considerations, such as cloud-based versus on-premise solutions (LO11, LO12). In addition, students were expected to discuss potential risks, including AI security, ethical concerns, and regulatory compliance (LO17, LO18, LO38, LO39), and propose strategies for effective risk mitigation. A key aspect of this assignment involved evaluating stakeholder engagement, where students had to outline strategies for change management, cross-functional collaboration, and organisational adoption (LO40).

The module's assessment framework aimed to ensure that students developed both technical AI capabilities and strategic business acumen. By integrating practical model development with strategic planning, the assignments provided a well-rounded evaluation of students' ability to apply AI in business contexts. Ultimately, this assessment was designed to enable students to demonstrate their AI Capital, that is, the combined technical proficiency and strategic insight required for responsible, value-driven AI deployment in contemporary businesses.

4.5 Pedagogical principles and innovations in the AI Business Environments module

This section outlines the pedagogical foundations, delivery strategies, and innovations underpinning the AI in Business Environments module. It begins with an overview of the learning

theories that informed the module's design (4.5.1), followed by a discussion of the inclusive practices applied in its delivery (4.5.2). The final subsection highlights key curricular and structural innovations and explains their alignment with the AI Learning–Capital–Employment Transition model (4.5.3).

4.5.1 Learning theories

The AI in Business Environments module reflects a carefully designed synthesis of constructivist and experiential pedagogical principles. It was developed to empower students from non-technical backgrounds with the AI-related knowledge, skills, and capabilities that collectively form AI Capital (Drydakis, 2024a). At its core, the module is grounded in Constructivist Learning Theory (Piaget, 1952; Vygotsky, 1978), which views learning as an active, contextualised process in which students construct understanding through interaction with their environment. This approach is particularly valuable for learners with limited prior exposure to technical content. By integrating real-world AI applications, hands-on coding sessions, and business simulation activities, the module enables students to construct understanding through practice and reflection, rather than passively receiving information.

These pedagogical strategies are further supported by Experiential Learning Theory (Kolb, 1984), which proposes that effective learning is achieved through iterative cycles of experience, reflection, conceptualisation, and experimentation. The module reinforces this framework through applied tasks such as developing classification models for customer segmentation and conducting fairness audits using explainable AI tools. These activities enable students to apply theoretical ideas in real-world contexts and reflect on both technical outcomes and ethical considerations.

The module also applies the principles of the Technological Pedagogical Content Knowledge framework (Mishra and Koehler, 2006), which emphasises integrating technological tools with pedagogical approaches and subject expertise. In this context, AI technologies such as machine learning models, neural networks, and natural language processing are introduced in ways that are educationally meaningful and relevant to the disciplinary needs of economics and business students. Learning objectives are aligned with the AI Capital of Students scale, ensuring that content delivery is coherent, progressive, and measurable across all core dimensions.

The module design also reflects the Zone of Proximal Development (Vygotsky, 1978), in which students are supported as they move from foundational tasks to more complex challenges. For instance, learners begin with data pre-processing techniques before advancing to the deployment of AI models on cloud platforms. This scaffolded approach promotes both independent learning and collaborative problem-solving. It helps students to develop technical proficiency while also building confidence, critical thinking, and digital autonomy.

The simultaneous adoption of the aforementioned pedagogic theories is essential to the AI in Business Environments module, as it ensures a holistic, inclusive, and pedagogically coherent approach to

AI education for non-technical learners. By integrating these perspectives, the module provides a layered and responsive learning experience that supports students in constructing meaning, applying knowledge through iterative practice, connecting technological tools to discipline-specific learning goals, and progressing through scaffolded support structures tailored to their developmental readiness. This multidimensional framework enables learners to acquire AI Capital not only as a set of technical skills, but as a capability grounded in critical thinking, ethical reflection, and business relevance, thereby fostering both academic development and future workplace readiness.

These theoretical foundations are embedded in the module's delivery, which prioritises accessibility and inclusion across diverse learner backgrounds.

4.5.2 Inclusive design and delivery in practice

The AI in Business Environments module is delivered through a pedagogically inclusive and student-centred approach. Informed by Universal Design for Learning (Capp, 2017), the module is designed to ensure that students from diverse academic, social, and demographic backgrounds engage meaningfully with AI and develop AI Capital within an equitable learning environment.

Inclusive access and eligibility are embedded into the module structure. Students from an economics background, including those without prior computing or STEM-based education, are eligible to enrol provided they have passed prerequisite modules in mathematics, statistics, and economics. No ranking thresholds are applied. Enrolment follows a first-come, first-served policy, with places communicated equally to all eligible students. This approach avoids gatekeeping based on prior academic performance and promotes a level playing field for students with varying academic profiles and levels of digital confidence.

The curriculum design supports accessibility for students across a range of skill levels. AI concepts are introduced in progressive stages, beginning with conceptual overviews and advancing towards more technical applications. Students are not required to have prior coding experience and receive support through live demonstrations, step-by-step exercises, and applied activities using accessible platforms such as Python, R, TensorFlow and scikit-learn. Topics that are relatively complex for the audience in question, such as neural networks, natural language processing and fairness auditing, are presented through case-based examples and scaffolded exercises. This approach enables students to build both understanding and confidence incrementally.

The module employs multimodal content delivery in line with Universal Design for Learning principles. Materials are provided through a blend of lectures, seminars, live coding tutorials, infographics, videos and case studies. Practical sessions in computer laboratories complement theoretical lectures, allowing students to test and apply new concepts in real time. This multimodal approach reduces cognitive barriers and allows students to engage through formats best suited to their learning preferences

and prior experience. All materials are made available through the university's digital learning platform for asynchronous access, increasing flexibility and accessibility.

Pedagogical strategies promote inclusion at every stage. Students work in small, rotating groups on real-world problems drawn from a range of business and economics contexts, such as financial forecasting, customer segmentation and AI ethics. Group-based assignments encourage peer learning, reduce the isolation that can occur with technical content, and create opportunities for students with lower initial confidence to develop digital skills collaboratively. Feedback is continuous and formative, with clear marking criteria that recognise both technical proficiency and ethical insight.

Ethical reasoning and critical reflection are integrated as core components of AI Capital development. Students examine the ethical, social and governance dimensions of AI, including algorithmic bias, surveillance and fairness constraints. Readings and seminar discussions incorporate feminist, decolonial and anti-racist critiques. This provides students with tools to evaluate the societal impacts of AI and ensures that AI Capital is conceptualised not only as a set of technical competencies but also as a foundation for ethical judgement and civic responsibility.

To support equity in learning outcomes, students receive structured assistance throughout the module. This includes access to recorded tutorials, weekly coding seminars, drop-in support sessions and personalised feedback on assignments. The assignment structure reflects the inclusive ethos of the module by valuing strategic reasoning and conceptual insight equally alongside technical modelling and data analysis. The delivery of the module is informed by learning analytics and pedagogical research. Data collected across four cohorts, including AI Capital pre- and post-intervention scores, performance metrics and engagement indicators, are used to refine teaching practices, identify students' support needs and address disparities related to gender, ethnicity and academic background.

The delivery of the AI in Business Environments module demonstrates that inclusive design is not an additional consideration but a central pedagogical mechanism for shaping AI Capital. By embedding inclusive teaching into its structure, curriculum and assessment, the module provides an equitable platform for students to acquire the technical skills, ethical awareness and capabilities needed to participate in contemporary economic environments shaped by AI.

These inclusive strategies are further enhanced by a series of pedagogical innovations aligned with the AI Learning–Capital–Employment Transition model, as discussed in the next subsection.

4.5.3 Innovations

The AI in Business Environments module introduces several pedagogical and structural innovations that are closely aligned with the AI Learning–Capital–Employment Transition model. These innovations contribute to a distinctive, evidence-based approach to AI education that connects inclusive curriculum design, structured learning processes, the development of AI Capital and employment success.

One of the most significant innovations is the use of the validated and multidimensional AI Capital of Students scale to guide both instructional planning and student assessment. This tool allows educators to track the development of students' AI-related knowledge through objective tests and coursework results. This offers a more robust alternative to self-reporting and ensures alignment between intended learning outcomes, instructional content, and assessment criteria. The curriculum is purposefully structured to meet current labour market expectations. It includes applied content on AI-enabled decision-making, customer segmentation, forecasting, and risk modelling. Students engage with industry-relevant tools while also examining ethical, legal, and governance concerns. This integration ensures that graduates are prepared to lead and evaluate AI systems in diverse organisational settings. The delivery framework blends academic rigour with experiential learning. Students acquire transferable skills in coding, data interpretation, problem-solving, and collaborative planning. These are reinforced through lectures, seminars, and practical sessions. Graduate outcomes are monitored through post-completion tracking six months after graduation, enabling the evaluation of employability impact and the identification of areas for curriculum enhancement. Another notable innovation is the use of learning analytics to inform teaching design. Data from AI Capital assessments, objective testing, and coursework are used to measure individual and cohort progress. These insights guide adjustments to pedagogy, including content sequencing, feedback design, and the provision of tailored support. The analysis of disparities by gender, ethnicity, and academic history ensures that differentiated instruction is used strategically to improve access and outcomes for all students.

These innovations are embedded within the AI Learning–Capital–Employment Transition model, which explains that AI training is associated with measurable AI knowledge, skills, capabilities, and employability outcomes. The model synthesises constructivist, experiential, and inclusive learning theories into a coherent structure. Learning is conceptualised not merely as the acquisition of knowledge, but as the formation of capital. Through real-world engagement, collaborative learning, and ethical reflection, students develop the competencies needed to apply AI critically and strategically in professional and civic settings. The model also recognises that AI capital formation can be shaped to an extent by students' prior academic performance and learning, social context, and institutional resources. Inclusive design, guided progression, and targeted support are therefore understood as necessary components of effective pedagogy. Student-centred teaching is positioned not simply as good practice, but as a means of promoting both social mobility and ethical technological development.

By embedding these innovations within a robust theoretical and empirical framework, the module establishes a new benchmark for AI education in higher education. It demonstrates that high-quality, inclusive, and future-facing AI instruction can be both academically rigorous and socially responsive. Taken together, the pedagogical design and curricular structure of the AI in Business Environments module present a replicable model for interdisciplinary AI education. The module fosters cognitive,

ethical, and strategic growth, contributing to both educational equity and graduate employability in the evolving digital economy.

The pedagogical design, inclusive delivery, and evidence-based innovations outlined in this section demonstrate that the AI in Business Environments module offers more than a technically focused curriculum. It exemplifies a strategic and socially responsive approach to AI education, centred on the formation of AI Capital. By aligning learning experiences with labour market needs, ethical awareness and inclusive teaching principles, the module provides a replicable model for preparing students to participate critically, confidently and ethically in AI-integrated work environments, in line with the principles of the AI Learning-Capital-Employment Transition model.

5. Data set and data gathering

The dataset contains information on students' sex, race, and academic performance in core modules (i.e. Mathematics, Empirical Methods, and Economics). Moreover, the dataset includes responses to the 40-item AI Capital of Students scale, completed by students both before and after undertaking the AI in Business Environments module.

In addition, the dataset includes results from a 120-question, multiple-answer test, henceforth referred to as the AI Capital test, which measures students' actual AI Capital, including their knowledge, skills, and capabilities, at two points in time: before and after the module. This test was developed to align directly with the 40 learning objectives outlined in Appendix Table II. Specifically, three multiple-answer questions (MAQs) were created for each item of the 40-item AI Capital of Students scale, ensuring that each objective was assessed in a multifaceted and targeted manner. This structure provided a comprehensive evaluation of students' AI Capital, extending beyond self-perceived abilities to measure actual performance and understanding.

Furthermore, the dataset includes students' module assignment grades, recorded at the end of the course, as detailed in the Module Assignments section. Inclusion of these three indicators is essential for a comprehensive evaluation of students' AI Capital development. The AI Capital of Students scale captures students' self-perceived AI-related knowledge, skills, and capabilities before and after the module. The AI Capital test scores objectively assess students' knowledge, skills, and capabilities in relation to specific learning objectives, identifying tangible improvements. Finally, the module assignment grades serve as a performance-based indicator of students' ability to apply AI concepts in practice. Collectively, these measures provide a robust assessment of learning outcomes by bridging self-reported perceptions, objective knowledge, and applied skills.

Students completed the 40-item AI Capital of Students scale and the 120-question AI Capital test during a three-hour in-class session. This was a closed-book, pencil-and-paper assessment administered both prior to the module's commencement and upon its completion (i.e. after assignment submission).

The formal module assignment was submitted electronically at the end of the course and assessed using predefined marking criteria. Marks were recorded digitally, and feedback was provided to students within a specified timeframe.

Importantly, the study collected follow-up information six months after students' graduation. This made it possible to classify students as employed, unemployed, or economically inactive. These data were used to assess whether an association between AI Capital and leavers' employment status could be identified.

6. Validation of the AI Capital of Students scale

In the Appendix, Table A.III presents the validation results for the AI Capital of Students scale, structured into two panels. Panel I examines the entire scale (40 items), while Panel II evaluates the scale based on its three thematic components: Knowledge (21 items), Skills (7 items), and Capabilities (12 items).

[**Appendix Table A.III**]

In Panel I, the overall scale demonstrates excellent internal consistency, with a Cronbach's Alpha (α) of 0.97, indicating a high degree of correlation among the scale items. The H Index for the full scale is 0.50, suggesting that the subcomponents are well-defined. The chi-squared to degrees of freedom ratio (χ^2/df) is 1.7, indicating a reasonable model fit. The Root Mean Square Error of Approximation (RMSEA) is 0.054, suggesting a good fit, as does the Standardised Root Mean Square Residual (SRMR = 0.041). The Normed Fit Index (NFI = 0.807), Relative Noncentrality Index (RNI = 0.910), Comparative Fit Index (CFI = 0.910), and Incremental Fit Index (IFI = 0.911) further support the structural validity of the scale (Hu and Bentler, 1999).

In Panel II, the thematic subscales also exhibit strong reliability. The Knowledge subscale (Theme A) has a Cronbach's Alpha of α = 0.95, reflecting very high internal consistency. Similar results are found for the Skills subscale (Theme B, α = 0.86) and the Capabilities subscale (Theme C, α = 0.90). The H Index values across the subscales are H = 0.50 for Knowledge, H = 0.49 for Skills, and H = 0.47 for Capabilities, indicating moderate scalability, with Knowledge displaying slightly stronger structural coherence. The chi-squared to degrees of freedom ratio (χ^2/df) is 1.7, again suggesting a good fit. The RMSEA is 0.053, and the SRMR score is 0.040, both pointing to an acceptable model fit. Additionally, the fit indices, NFI = 0.808, RNI = 0.911, CFI = 0.911, and IFI = 0.912, confirm a robust model structure.

The validation results for both the full scale and the thematic model are closely aligned, indicating that the subscales cohere well and reflect the broader construct. These outcomes confirm that the AI Capital of Students scale is a reliable and valid instrument for assessing students' AI-related knowledge, skills, and capabilities.

7. Descriptive statistics

Table 1 provides an overview of key variables related to students' demographic composition, academic performance, and AI-related outcomes. The sample consists predominantly of men (69.1%), and 75.8% of students identify as White. The proportion of students achieving a distinction is 32.5% in Mathematics, 34.1% in Empirical Methods, and 29.1% in Economics. In the UK higher education system, a mark of 40% is typically the minimum threshold to pass an undergraduate module, while 70% or above is generally required for a distinction. The data also indicate that, six months after graduation, 44.1% of the students were employed, 14.1% were unemployed, and 41.6% were economically inactive (half of whom were enrolled in postgraduate studies).

In the total sample, i.e. before and after the AI in Business Environments module, the mean score on the AI Capital of Students scale is 75.9 (out of 200), indicating a moderate average score. However, the large standard deviation (26.5) suggests substantial variation in students' AI-related knowledge, skills, and capabilities. Additionally, based on the AI Capital test scores, the mean AI Capital score is 39.8 (out of 100), with a standard deviation of 18.9. The mean grade in the AI in Business Environments module is 54.7 (out of 100), with a standard deviation of 14.6. This average indicates a modest level of performance, accompanied by considerable variation. Every student in the sample successfully passed the AI in Business Environments module.

[Table 1]

In the Appendix, Table A.I presents the AI Capital of Students scale, showing the mean scores and standard deviations for each of the 40 items before and after the AI training (i.e., the AI in Business Environments module). The table captures students' self-reported knowledge, skills, and capabilities across multiple AI themes, with improvements assessed using t-tests. The results highlight the effectiveness of the AI in Business Environments module in enhancing AI knowledge, skills, and the capability to leverage AI for business applications.

For instance, Item 1 of the scale showed a significant improvement in students' understanding of how to distinguish between key AI-related concepts following the training (1.37 vs 2.35, $p < 0.01$). Initially, students reported limited understanding of how to differentiate AI from related fields such as machine learning, deep learning, and automation. However, post-training scores indicated a notable increase in understanding, suggesting that the module effectively clarified foundational AI concepts, thereby demonstrating an improvement in students' AI-related knowledge. Moreover, Item 24 revealed one of the most substantial improvements, with students reporting increased use of programming languages such as Python and R for AI model development (1.20 vs 2.38, $p < 0.01$). This marked enhancement in skills suggests that the training offered meaningful hands-on coding experience, which is essential for applying AI in business contexts.

In addition, Item 32 showed significant progress in students' capability to use AI to create competitive advantages, such as delivering personalised customer experiences and implementing targeted marketing strategies (1.20 vs 2.30, $p < 0.01$). The substantial post-training gains suggest that the module positioned AI not merely as a technological tool, but as a driver of efficiency and innovation.

Table 2 presents a tabulated analysis of the AI Capital of Students scale (Panel I), the AI Capital test scores (Panel II), and students' average grade in the AI in Business Environments module (Panel III). The results are segmented by AI training periods, i.e. before and after the AI in Business Environments module, as well as by gender, ethnicity, and academic distinctions. The table also reports t-tests, indicating whether the differences between groups are statistically significant.

The AI Capital of Students scale score increased significantly from 53.7 to 98.1 (out of 200) following the training ($p < 0.01$), indicating a strong positive effect of the AI in Business Environments module. Similarly, students' AI Capital test score showed a substantial increase, from 25.6 to 54.0 (out of 100) ($p < 0.01$), suggesting that the training effectively enhanced students' AI-related knowledge, skills, and capabilities.

The results further show that men, White students, and those who achieved distinctions in Mathematics, Empirical Methods, or Economics scored significantly higher than women, non-White students, and those without academic distinctions across the AI Capital of Students AI scale ($p < 0.01$), the AI Capital test scores, and the module grades. These findings suggest the presence of a gender and ethnicity-related gap in AI-related knowledge and performance.

Additional insights indicate that, six months after graduation, students in employment score significantly higher on the AI Capital of Students scale, the AI Capital test, and their average grades in the AI in Business Environments module than those who are unemployed or economically inactive (all $p < 0.01$).

[Table 2]

Table 3 presents a correlation matrix. The AI Capital of Students scale is highly correlated with its subcomponents: Knowledge ($r = 0.98$, $p < 0.01$), Skills ($r = 0.94$, $p < 0.01$), and Capabilities ($r = 0.97$, $p < 0.01$). These strong correlations suggest considerable interrelation among the dimensions, indicating that students' AI-related knowledge, skills, and capabilities are closely linked. In addition, the AI Capital test scores also show a strong correlation with the overall AI Capital of Students scale ($r = 0.91$, $p < 0.01$) and its subcomponents, confirming the internal consistency of the AI Capital measurement.

Furthermore, the findings indicate that AI training is significantly correlated with students' AI Capital levels. Specifically, the post-training period is positively correlated with both the AI Capital of Students scale ($r = 0.83$, $p < 0.01$) and the AI Capital test scores ($r = 0.74$, $p < 0.01$). Moreover, the AI Capital of Students scale is positively correlated with students' grades in the AI in Business Environments module ($r = 0.76$, $p < 0.01$), suggesting that the development of students' AI Capital is associated with

improved performance in AI-related assessments. Finally, a positive correlation is also found between the AI Capital of Students scale and individuals' employment rate six months after graduation ($r = 0.546$, $p < 0.01$).

[Table 3]

8. Estimates

8.1 Estimation strategy

Table 4 presents the regression results from various model specifications, assessing whether students experience improvements in the AI Capital of Students scale and in their AI Capital test scores following AI training through the AI in Business Environments module. Given the nature of the data, the study employs three empirical approaches: Pooled Ordinary Least Squares (OLS) models, Random Effects models, and Fixed Effects models (Bell et al., 2019). Panel data specifications are particularly suited to capturing within-individual variation over time, offering advantages over cross-sectional models. However, in Random Effects models, omitted variables may be correlated with key predictors, introducing potential bias. By contrast, Fixed Effects models control for time-invariant unobserved heterogeneity, thereby reducing omitted variable bias (Vaisey and Miles, 2017). To determine the most appropriate empirical specification, the Breusch and Pagan Lagrangian Multiplier test is used to compare Pooled OLS and Random Effects estimates, while the Hausman test assesses the efficiency and consistency of Random versus Fixed Effects models[1].

To address potential endogeneity and omitted variable bias, the regression analysis includes controls for achievement in mathematics, empirical methods, and economics, as distinctions in these subjects may be associated with academic performance. Demographic characteristics (sex and ethnicity) are also included to account for potential disparities in AI learning outcomes (Clarke, 2005). Controlling for these factors allows the estimated associations to more accurately reflect the impact of AI training rather than pre-existing individual advantages.

[1] In Table 4, prior to conducting the regression analyses, the underlying assumptions of the models employed were evaluated. Linearity was assessed using residual-versus-fitted value plots, multicollinearity was examined through Variance Inflation Factors (VIFs), and homoscedasticity was tested using the Breusch–Pagan test. VIF values remained below the conventional threshold of 10, indicating no evidence of problematic multicollinearity. The residual plots suggested an approximately linear relationship between the predictors and the outcomes, and the Breusch–Pagan test did not indicate the presence of heteroscedasticity. The normality of residuals was examined using Q–Q plots, which showed no substantial deviations from normality.

Beyond the primary regressions, Table 4 also reports OLS models examining the association between the AI Capital of Students scale and students' grades in the AI in Business Environments module, exploring whether AI Capital is related to academic success. Additionally, Table 5 disaggregates AI Capital into its components, knowledge, skills, and capabilities, to assess their individual contributions. This step enables an evaluation of whether students experience targeted improvements in specific areas of AI Capital following the training. These additional analyses strengthen the validity and generalisability of the findings, offering further insight into how AI training affects students' knowledge and academic performance. Moreover, Table 6 presents regressions by gender and ethnicity, investigating whether all demographic groups in the sample experience gains in AI Capital after the training. These specifications enhance the robustness and inclusivity of the results.

Finally, Table 7 examines whether students' AI Capital, measured using alternative indicators (i.e. the AI Capital of Students scale, AI Capital test scores, and the grades achieved in the AI in Business Environments module), is associated with their employment outcomes, using Probit models[2]. These evaluations offer additional insights into the potential benefits that AI Capital may provide for students.

8.2 Outcomes

Table 4 presents regression results across eight models, evaluating the AI Capital of Students scale (Models I–III), students' AI Capital test scores (Models IV–VI), and grades in the AI in Business Environments module (Models VII and VIII). Models I–III report regression estimates for the AI Capital of Students scale using Pooled Ordinary Least Squares (OLS), Random Effects, and Fixed Effects models. Across all three models, the results indicate that students' AI Capital increases significantly following the training. The coefficient ($b = 44.425$, $p < 0.01$) consistently suggests a substantial improvement in students' AI Capital after completing the AI in Business Environments module. The Breusch and Pagan Lagrangian Multiplier test confirms that the Random Effects model is preferable to Pooled OLS ($p < 0.01$). The Hausman test ($p > 0.10$) suggests that the Random Effects model is more efficient and appropriate than the Fixed Effects model. The Random Effects estimates further reveal that

[2] For the Probit models presented in Table 7, the study evaluated the key assumptions underlying non-linear binary response models. Multicollinearity was assessed by computing Variance Inflation Factors from auxiliary OLS regressions of the predictors, which indicated no problematic collinearity. To confirm appropriate model specification, link tests were conducted, and predicted employment outcomes were compared with observed outcomes as a model validation check. The independence of observations was ensured through the individual-level structure of the dataset. Model fit was assessed using pseudo R^2 values and likelihood ratio chi-squared statistics, both of which indicated explanatory power. These diagnostic procedures suggest that the assumptions of the Probit models were satisfactorily met.

male students ($b = 6.675$, $p < 0.01$), White students ($b = 7.172$, $p < 0.01$), and students who attained distinctions in Mathematics ($b = 8.144$, $p < 0.01$), Empirical Methods ($b = 5.333$, $p < 0.05$), and Economics ($b = 8.031$, $p < 0.01$) tend to achieve significantly higher scores on the AI Capital of Students scale.

[Table 4]

Models IV–VI present regression estimates for the AI Capital test scores, using Pooled Ordinary Least Squares (OLS), Random Effects, and Fixed Effects models. The coefficient ($b = 28.358$, $p < 0.01$) across all three models indicates a significant improvement in students' AI Capital test scores following the training. Both the Breusch and Pagan Lagrangian Multiplier test and the Hausman test suggest that the Random Effects model is more efficient than the Pooled OLS and Fixed Effects models. The Random Effects estimates further show that male students ($b = 6.177$, $p < 0.01$), White students ($b = 6.485$, $p < 0.01$), and students who achieved distinctions in Mathematics ($b = 8.925$, $p < 0.01$) and Economics ($b = 8.163$, $p < 0.01$) tend to obtain significantly higher AI Capital test scores.

Models VII–VIII present regression estimates for students' grades in the AI in Business Environments module, using Pooled Ordinary Least Squares (OLS) models. In Model VII, the results suggest that several factors are associated with higher grades. Male students ($b = 7.672$, $p < 0.01$), White students ($b = 4.779$, $p < 0.05$), and those who achieved distinctions in Mathematics ($b = 9.871$, $p < 0.01$), Empirical Methods ($b = 10.550$, $p < 0.01$), and Economics ($b = 3.916$, $p < 0.10$) tend to perform better in the module. In Model VIII, the AI Capital of Students scale is included as a predictor, with a positive and statistically significant coefficient ($b = 0.302$, $p < 0.01$), indicating that students with higher AI Capital scores are more likely to achieve better academic performance in the AI in Business Environments module.

Table 5 evaluates how different components of AI Capital, i.e., Knowledge, Skills, and Capabilities, are influenced by AI training. All models present Random Effects regression estimates, as this specification was found to provide the best fit for the data. The results indicate that AI training delivered through the AI in Business Environments module is associated with a significant increase in AI Knowledge in Model I ($b = 23.558$, $p < 0.01$), enhanced AI Skills in Model II ($b = 7.508$, $p < 0.01$), and increased AI Capabilities in Model III ($b = 13.358$, $p < 0.01$). Across all models, it is observed that male and White students, as well as those who achieved distinctions in Mathematics, Empirical Methods, and Economics, tend to report higher levels of AI Knowledge, Skills, and Capabilities.

[Table 5]

In Table 6, Models I and II show that, following AI training, both male and female students exhibit increased levels of AI Capital, as measured by the AI Capital of Students scale ($b = 45.975$, $p < 0.01$ and $b = 40.945$, $p < 0.01$, respectively), although the coefficient is higher for male students. Similarly, in Models III and IV, both White and non-White students demonstrate improvements in AI Capital after the

training (b = 45.538, p < 0.01 and b = 40.931, p < 0.01, respectively), with a larger effect observed among White students. All models report Random Effects regression estimates, as this specification was found to provide the best fit for the data. Comparable patterns are observed when the AI Capital test scores are used instead of the AI Capital of Students scale.

[Table 6]

Table 7 presents employment estimates. Probit models, reporting marginal effects, are shown. In Model I, an increase in the level of AI Capital of Student scale is associated with higher employment rates (b = 0.013, p < 0.05). Similarly, Model II shows a positive association between the AI Capital test scores and students' employment rates (b = 0.053, p < 0.01). Furthermore, Model III estimates a positive association between the grades in the AI in Business Environments module and employment rates (b = 0.057, p < 0.01). These outcomes hold after controlling for key heterogeneities related to gender, race, and degree classification.

[Table 7]

9. Discussion

9.1 Outcomes evaluation

This study aimed to develop and validate the AI Capital of Students scale, offering a structured framework for assessing non-STEM university students' AI-related knowledge, skills, and capabilities. The findings confirm that AI education contributes to the development of students' AI Capital by enhancing both theoretical understanding and practical application skills. These results are consistent with recent research across Europe, Asia, and North America (Biagini, 2025; Bewersdorff et al., 2025; Chiu et al., 2024; Hornberger et al., 2023; Wang et al., 2023; Kong et al., 2021, 2022, 2023). Nonetheless, observed disparities in learning outcomes underscore the importance of adopting more inclusive and equitable approaches to AI training.

This section reflects on each research question in relation to the study's key findings. The first research question aimed to identify the key elements within the three dimensions of AI Capital, knowledge, skills, and capabilities, each playing a distinct role in preparing students for AI-integrated workplaces. AI knowledge was defined in terms of fundamental AI concepts such as machine learning, neural networks, and data analytics. AI skills were framed around programming, model development, and technical proficiency. AI capabilities were envisioned as the ability to integrate AI into business decision-making and to develop an understanding of AI's strategic application. The study highlights the need for AI education to strike a balance between theoretical instruction and applied practice. While knowledge acquisition can occur relatively quickly, developing strong AI skills and capabilities requires more sustained exposure to real-world AI applications (Drydakis, 2024a).

The second research question examined how AI Capital among university students can be effectively measured. The successful validation of the proposed AI Capital of Students scale demonstrates its value as a robust tool for assessing students' AI-related knowledge, skills, and capabilities. This scale allows educators to monitor progress over time and evaluate the impact of AI training programmes. By capturing both students' self-perceptions of AI Capital and objective indicators of AI Capital, the tool provides a comprehensive assessment of learning outcomes. The study underscores the value of measuring multiple dimensions of AI Capital, recognising that students' confidence in their knowledge is as important as their technical abilities, such as programming and model evaluation. Access to this type of data is essential for educators seeking to evaluate curricula and monitor student development effectively.

The third research question examined the extent to which AI education enhances students' AI Capital. The findings confirm that AI education significantly enhances students' AI Capital, with improvements observed across all three dimensions. This was assessed using the AI Capital of Students scale, as well as through tests measuring objective levels of AI Capital. Robustness evaluations indicated that these improvements were observed among both male and female students, as well as among White and non-White students. The fourth research question focused on the relationship between students' AI Capital and their academic performance. The findings reveal a clear link between AI Capital and academic success, indicating that students who develop stronger AI-related knowledge, skills, and capabilities tend to perform better in AI-related coursework. This reinforces the idea that AI Capital is not merely an abstract concept but has direct academic benefits.

The fifth research question explored how demographic and academic factors influence variations in students' AI Capital. Male and White students achieved higher AI Capital scores, while students with strong backgrounds in mathematics, empirical methods, and economics also performed better. These patterns reflect broader trends in science and technology education, where prior exposure to and confidence in technical subjects play a critical role in shaping learning outcomes. The findings suggest that gaps in AI Capital may emerge well before university-level training, reinforcing the need for early exposure to AI concepts and digital skills within the education system. This observation further highlights the importance of incorporating targeted interventions within AI education to support underrepresented groups and address structural inequalities.

The sixth research question aimed to assess whether students' AI Capital is associated with their employment levels. A positive relationship was identified, suggesting that higher levels of AI Capital are linked to improved employment outcomes among graduates. By treating AI Capital as a measurable and developable resource, the study highlights the importance of embedding AI education within curricula not only to foster technical literacy, but also to facilitate students' transition into the workforce. Enhancing students' knowledge, skills, and capabilities related to AI and its applications equips them to meet

evolving labour market demands, secure employment in digitally intensive roles, and contribute to innovation-driven sectors.

The findings validate the AI Learning–Capital–Employment Transition model introduced in this study. By integrating the conceptual foundations of AI Capital with empirical evidence on academic performance, and employment outcomes, the model offers a coherent and evidence-based framework for curriculum design. It demonstrates that structured and inclusive AI education, as illustrated by the AI in Business Environments module, supports the development of AI Capital and enhances students' prospects in the labour market. In doing so, the model positions AI Capital both as a tool for assessing student development and as a pedagogical goal aligned with the demands of an AI-integrated economy. It also highlights the importance of equity-centred educational strategies to ensure that all students, regardless of background, can benefit from AI training. As universities adapt to the digital transformation of work, this model provides a practical foundation for embedding AI literacy into higher education policy and practice.

9.2 Contributions

This study introduces a key theoretical innovation through the application of the AI Capital framework. Unlike previous research, which has largely defined AI literacy in terms of cognitive knowledge, ethical awareness, or general familiarity with AI, this study reconceptualises AI literacy as a multidimensional form of capital. Drawing on Drydakis' (2024a) theory of AI Capital, it integrates knowledge, skills, and capabilities, framing AI literacy as a strategic asset for students entering AI-mediated work environments. This reconceptualisation marks a significant advancement over dominant narratives in the existing literature, which often treat technical or ethical capabilities in isolation from their practical application. In contrast, the AI Capital framework evaluated in this study directly links AI literacy to academic performance and employability. It addresses a critical gap by explicitly connecting AI education to economic value and strategic relevance, dimensions that have been largely overlooked. Furthermore, the study contributes to theoretical development by empirically demonstrating that students with higher levels of AI Capital performed significantly better in AI-related coursework. This provides evidence that AI literacy, when framed as capital, is not only a theoretical construct but also a predictor of educational success, adding a new empirical dimension to ongoing debates surrounding the role and value of AI education in higher education and labour market preparation.

This study also advances the field through a number of methodological innovations. Most notably, it developed and validated the AI Capital of Students scale, a comprehensive measurement tool specifically designed for students in non-STEM disciplines. The scale captures three interconnected dimensions: conceptual knowledge, technical skills, and strategic capability. Its development and validation involved factor analysis, offering a more rigorous approach than the reliance on Cronbach's

alpha observed in earlier studies. This enhanced the scale's construct validity and reliability, confirming its suitability for capturing the complexity of AI literacy in applied contexts. In addition, the study adopted a longitudinal and multi-method design, distinguishing it from the majority of AI literacy research. It employed three distinct data sources to assess changes in AI Capital before and after training: (1) AI Capital of Students scale responses, (2) an objective AI Capital test, and (3) actual academic performance, as reflected in grades from an AI-related module. This approach contrasts with the single-wave, descriptive designs common in earlier research, which do not track learning progress or allow for robust inference. By doing so, the study was able to assess students' actual AI Capital, rather than relying solely on perceived or potential AI literacy. Most notably, the study employed panel regression models, using both random effects and fixed effects estimations to control for unobserved individual-specific characteristics and cohort-level differences. Such econometric techniques, which support causal inference, are rare in this field. As a result, this research stands out as one of the first to adopt causal econometric methods, offering robust evidence that AI education can directly improve AI Capital.

In addition to its theoretical and methodological value, the study offers several practical contributions that can inform AI curriculum design and educational policy. The most significant of these is the design, delivery and evaluation of the AI in Business Environments module, created specifically for undergraduate economics students. Unlike the generic or non-evaluated interventions found in the existing literature, this module was tailored to address the specific academic and professional development needs of certain professional student groups. Each week was designed around clear learning objectives aligned with the three components of AI Capital: knowledge (e.g., understanding algorithms and AI frameworks); skills (e.g., developing hands-on experience with data processing and visualisation tools); and capabilities (e.g., making strategic business decisions using AI insights). This intervention ensured that students were not only exposed to theoretical content but were also actively developing practical, transferable skills aligned with labour market demands. The impact of the module was evaluated using a pre-post design, which revealed statistically significant improvements across all three dimensions of AI Capital. These findings demonstrate that discipline-specific AI education can produce measurable, meaningful outcomes, offering a replicable and scalable model for universities seeking to embed AI training within non-STEM curricula.

Importantly, by evaluating the positive association between AI Capital and graduates' employment prospects, the study highlights the significance of AI education interventions for university students. The research design played a crucial role in strengthening the robustness of the findings by reducing the influence of unobserved student heterogeneities. Specifically, the association was examined among students enrolled in the same university course, ensuring a relatively homogeneous sample in terms of pre-university educational attainment, as all participants met comparable course entry requirements (Drydakis, 2016). Furthermore, all students demonstrated a clear interest in AI technologies,

as evidenced by their enrolment in and successful completion of the AI in Business Environments module. These design features helped to minimise the impact of unobserved individual preferences or motivational differences, allowing for a more reliable assessment of the link between AI Capital and employment outcomes (Drydakis, 2015). By accounting for such factors, the study provides a more precise and internally valid evaluation of an important research question, namely, whether AI Capital can be regarded as a strategic and developable asset that enhances graduates' labour market success.

Taken together, the theoretical, methodological, and practical contributions of this study reinforce the broader relevance of the AI Learning–Capital–Employment Transition model. It presents a pedagogically grounded and outcome-focused approach that connects AI education with academic attainment and employability. By outlining a clear pathway from education to employment, it contributes to curriculum design and institutional planning, offering a strategic response to the growing demand for AI-literate graduates.

9.3 Implications for educational theory and pedagogical practice

Building on the earlier analysis, the AI in Business Environments module offers a compelling example of how diverse pedagogical frameworks can inform the design of inclusive and academically rigorous curricula in higher education. This section explores the theoretical and practical implications of applying constructivist, experiential, and inclusive approaches to AI Capital development, particularly in contexts where students may have limited prior technical experience.

Constructivist Learning Theory (Piaget, 1952; Vygotsky, 1978) informed the module's emphasis on active engagement, with students working with AI tools through project-based tasks, applied case studies, peer learning and computer-led seminars. These activities encouraged learners to construct understanding through participation and collaborative exploration. This approach counters the view that constructivist methods are only effective in exploratory or informal learning settings. When accompanied by appropriate scaffolding, constructivist strategies supported knowledge construction and problem-solving, even in technically intensive tasks. Learners with limited experience in programming, statistics, or AI particularly benefitted from this structure, progressing from initial uncertainty to greater confidence and capability. The module thereby reinforces the utility of Constructivist Learning Theory in higher education and demonstrates its adaptability to cognitive demands beyond foundational learning. It also highlights the value of designing active learning environments that foster inquiry, dialogue, and application among diverse learners.

Experiential Learning Theory (Kolb, 1984) was evident in how learning activities were sequenced. Students first engaged with theoretical content, reflected on its application to real-world business challenges, implemented AI tools in practice, and refined their outputs based on feedback. The cycle of experience, reflection, action, and revision was central to the module's structure. Although

Experiential Learning Theory is widely applied in leadership and interpersonal skills training, its principles are equally valuable for technical and domain-specific education, where embedding them in applied tasks and reflective cycles fosters deeper understanding, skill development and learner autonomy. Its strength lies in bridging conceptual understanding with hands-on experimentation, supporting students in retaining knowledge and transferring it across tasks. The module demonstrates how experiential AI learning can enhance AI technical education, particularly when assessments are aligned with each stage of the learning process and learners are encouraged to iterate and refine their work.

The Technological Pedagogical Content Knowledge framework (Mishra and Koehler, 2006) was reflected in the integration of digital tools, subject matter, and pedagogy. Technologies such as coding platforms and cloud-based systems were not treated as optional enhancements but embedded directly into learning objectives and assessments. This integration ensured coherence between what was taught, how it was taught, and the tools used to support it. Technological Pedagogical Content Knowledge's relevance in technically demanding fields such as economics and AI is affirmed by this approach, which required learners to apply domain knowledge through digital tools in ways that mirrored industry practice. The AI in Business Environments module thus illustrates how technology-enhanced pedagogy can preserve academic rigour while simultaneously fostering student engagement and strengthening real-world relevance.

The principle of scaffolding, drawn from the Zone of Proximal Development (Vygotsky, 1978), was operationalised through tiered support mechanisms. These included guided coding tasks, opportunities for peer learning, and real-life business assessments. For students unfamiliar with STEM disciplines, such support was critical in enabling meaningful engagement with complex material. While learners with prior experience could progress quickly, those with less confidence benefited from structured interventions that helped to close initial knowledge gaps. The findings illustrate how Zone of Proximal Development-informed teaching can reduce disparities and ensure that students with varying levels of prior knowledge are supported through appropriate guidance. In contexts requiring mastery of technical content, such differentiated support remains essential to achieving equitable learning outcomes.

The Universal Design for Learning framework (Capp, 2017) was embedded in the diversity of teaching formats and assessment methods. The module incorporated lectures, coding labs, and seminars, alongside both technical projects and strategic written outputs. Support strategies were also tailored to accommodate varied educational backgrounds and lived experiences. By analysing outcomes by gender, ethnicity, and prior attainment, the design team was able to identify patterns of engagement and adjust the delivery accordingly. This proactive approach ensured that learning remained accessible and meaningful for all students, including those with no prior familiarity with AI concepts. Rather than functioning as an add-on, inclusive design was a foundational element that enhanced the module's accessibility and responsiveness. Universal Design for Learning thus supported the creation of an equitable and engaging

learning environment, a consideration of particular importance in disciplines characterised by rapid technological change.

In summary, the AI in Business Environments module illustrates how constructivist, experiential, inclusive, and scaffolded teaching approaches can be combined to enable the effective delivery of AI education to students from non-technical backgrounds. The study contributes to educational theory by reaffirming the relevance of these frameworks in contemporary, digitally mediated learning environments and by extending their use to technical subjects often perceived as inaccessible to non-specialist learners. From a pedagogical standpoint, the module serves as a framework for designing inclusive and discipline-specific curricula that promote engagement, support progression, and strengthen skills transfer.

Crucially, this approach aligns with the AI Learning–Capital–Employment Transition model, which highlights the development of AI Capital and its role in enhancing employment prospects. The pedagogical principles used in the module are directly associated with the formation of AI Capital and improved employment outcomes, highlighting their importance in equipping learners to engage with emerging technologies and to achieve both learning and labour market success.

9.4 Policy Implications

For universities, the findings support the integration of AI modules across faculties, not only within STEM disciplines, but also in the social sciences, to enhance students' employment outcomes (Drydakis, 2025a). This aligns with calls to embed AI literacy across a wide range of curricula, ensuring that students from all academic backgrounds have the opportunity to develop essential digital capabilities (Kong et al., 2023; Chiu et al., 2024; Biagini, 2025). The AI Capital framework adopted in this study offers a clear model for curriculum development, combining foundational knowledge with applied skills and capabilities. Universities should design equity-informed AI interventions that are sensitive to students' prior exposure to technical subjects such as mathematics, computing, and statistics.

As demonstrated by this study and supported by the literature (Bewersdorff et al., 2025; Hornberger et al., 2023), students with weaker quantitative backgrounds often exhibit lower levels of AI literacy. Preparatory programmes could be introduced to equip these students with the quantitative and technical foundations necessary to succeed in AI-integrated courses. Such measures would help ensure that students' prior academic training does not become a barrier to AI learning. Similarly, addressing demographic disparities in AI Capital development requires inclusive and targeted teaching practices. This study identified differences in AI Capital outcomes across gender and ethnic groups. In light of these findings, universities should implement mentorship schemes specifically aimed at supporting women and students from underrepresented ethnic groups in technology-focused learning. Faculty development in inclusive pedagogy, the use of diverse case studies, and the integration of ethical and societal dimensions

of AI can also enhance engagement among students who might otherwise feel marginalised or disconnected from technical content.

For policymakers, the results highlight the need for increased investment in AI education at the tertiary level, with a focus on building institutional capacity to deliver interdisciplinary AI modules (Drydakis, 2025a). This includes funding for educator training, access to high-quality AI tools and platforms, and incentives for universities to embed AI literacy across the curriculum. As noted in the literature (Drydakis, 2025a; Kong et al., 2021), well-funded AI programmes that utilise visual or no-code AI tools have proven effective in democratising access to AI and empowering students from non-technical backgrounds. National and regional education strategies should prioritise the formation of AI Capital as a core capability for graduate employability and economic resilience, particularly in sectors undergoing digital transformation (Drydakis, 2025a). Policymakers should also establish monitoring frameworks to track digital inclusion and evaluate the outcomes of AI education initiatives. These frameworks should promote the collection and disaggregation of data on students' AI performance by gender, ethnicity, prior educational background, and socioeconomic status. Doing so will help ensure that interventions are equitable and will guide the strategic allocation of public resources to areas of greatest need.

For students, particularly those from non-STEM or underrepresented backgrounds, this study offers a clear message: AI Capital is not only attainable but also constitutes a key driver of both academic performance and employability. As evidenced in this research and the wider literature (Drydakis, 2024a), students who actively engage with AI modules report stronger academic outcomes and are viewed more favourably by employers. Students should be encouraged to pursue AI modules regardless of their initial level of technical confidence. Universities and student support services can play a vital role in building this confidence through AI orientation sessions, peer-led learning communities, and the promotion of diverse role models who have successfully navigated AI-intensive fields.

Similarly, embedding AI content into university curricula, particularly within non-technical disciplines, can help to futureproof graduates against skills mismatches in rapidly evolving job markets. The findings of this study suggest that AI Capital now constitute a distinct form of capital that is increasingly vital to employability (Drydakis, 2025a). This form of capital is particularly valuable to firms given the growing demand for efficiency, productivity, innovation, and responsiveness to emerging technologies. Consequently, policymakers should support the integration of AI-focused modules across a wider range of university programmes. More broadly, initiatives that promote AI education can also enhance social mobility by enabling graduates from diverse backgrounds to access higher-paying and more resilient employment opportunities (Drydakis, 2024a).

9.5 Limitations and future research

While this study makes significant theoretical, empirical, and practical contributions to understanding AI education in higher education, several limitations should be acknowledged. These limitations provide important directions for future research and potential extensions. First, the study was conducted at a single university in England and focused specifically on students studying economics. This limited scope may restrict the generalisability of the findings across disciplines, institutions, and geographic regions. Students in other academic fields, such as the humanities or health sciences, may possess different levels of preparedness, digital capabilities, and responses to AI training. Moreover, regional and institutional differences in resources and pedagogical emphasis could influence outcomes. Future research should include multi-institutional samples from across the UK, as well as international contexts, to capture a broader and more diverse range of student experiences. Comparative analyses across institutions and countries would help identify how contextual factors shape the development of AI Capital and the effectiveness of AI education interventions.

Second, the study did not evaluate the effectiveness of alternative pedagogical approaches. Future research should experimentally test a range of teaching interventions, ideally using randomised or quasi-experimental designs, to determine which methods are most effective for different student groups, particularly those with limited prior exposure to technical subjects. Third, the study did not account for variation in institutional or instructor-level factors, such as teaching quality, resource availability, or AI infrastructure. These differences may significantly influence student engagement and learning outcomes. Multi-level modelling approaches in future studies could help identify the relative importance of institutional context, pedagogical practices, and departmental support in shaping the development of AI Capital. Fourth, the study only evaluated the employment outcomes of students who enrolled in the AI in Business Environments module. Future research should assess AI Capital in broader student populations to test the robustness of the observed pattern across alternative settings.

Finally, the study did not incorporate students' personality traits, such as conscientiousness, openness to experience, or self-efficacy, which may influence AI learning. Nor did it include students' socioeconomic backgrounds in the empirical analysis. These factors may act as important mediators or moderators in explaining variation in the formation of AI Capital, especially given known inequalities in digital access and confidence. Future research should collect data on psychological and socioeconomic characteristics and explore how these interact with demographic and academic variables. Doing so would enable the development of more targeted and equitable policy interventions.

10. Conclusions

This study reports on a 12-week university module designed to build students' AI Capital, delivered on four occasions between 2023 and 2024. A central component of the research was the development and validation of the AI Capital of Students scale, which provides a reliable framework for

measuring students' AI-related knowledge, skills, and capabilities. The results confirmed that structured AI education significantly enhances students' AI Capital, as evidenced by both self-assessed and objectively tested measures. Moreover, AI Capital was positively associated with academic performance, as evidenced by students' module grades, and was linked to improved employment outcome. To provide a theoretical foundation for this pedagogical intervention, the study introduced and validated the AI Learning–Capital–Employment Transition model, which integrates pedagogical theory, empirical evidence, and structural considerations. The model provides a coherent explanation of how inclusive and constructivist AI education contributes to the accumulation of AI Capital and supports students' transition into AI-integrated labour markets. By linking curriculum design, learning processes, and employment outcomes, the model offers a novel contribution to both educational research and institutional planning.

However, the study also identified disparities in outcomes. Male students, White students, and those with stronger foundations in mathematics, empirical methods, and economics achieved higher AI Capital scores and stronger academic results. These patterns reinforce the need to tailor AI education to account for variation in students' prior knowledge and digital confidence, ensuring that all learners can benefit equally from AI training. Overall, the study contributes new theoretical, methodological, and practical insights by conceptualising AI Capital as a measurable and developable strategic asset. The findings suggest that the development of AI Capital ought to be regarded not only as an educational objective but also as a policy priority. Embedding AI education across the curriculum, guided by the validated AI Learning–Capital–Employment Transition model, offers a scalable and inclusive approach to preparing students for success in digitally transformed workplaces. Ensuring equitable access to such training will be critical to shaping fair and future-ready higher education systems.

References

Agrawal, A., Gans, J., and Goldfarb, A. (2022). *Power and Prediction: The Disruptive Economics of Artificial Intelligence*. Brighton, Massachusetts: Harvard Business Press.

Becker, G. S. (1964). *Human Capital: A Theoretical And Empirical Analysis, With Special Reference To Education*. New York: Colombia University Press.

Bell, A., Fairbrother, M. and Jones, K. (2019). Fixed and Random Effects Models: Making an Informed Choice. *Quality and Quantity*, 53: 1051-1074.

Bewersdorff, A., Hornberger, M., Nerdel, C., and Schiff, D. S. (2025). AI Advocates and Cautious Critics: How AI Attitudes, AI Interest, Use of AI, and AI Literacy Build University Students' AI Self-Efficacy. *Computers and Education: Artificial Intelligence*, 8: 100340.

Biagini, G. (2025). Towards an AI-Literate Future: A Systematic Literature Review Exploring Education, Ethics, and Applications. *International Journal of Artificial Intelligence in Education*. https://doi.org/10.1007/s40593-025-00466-w

Bourdieu, P. (1983). Forms of Capital, in J. C. Richards (ed.). *Handbook of Theory and Research for the Sociology of Education* (241–258). NY: Greenwood Press.

Cachero, C., Tomás, D., and Pujol, F. A. (2025). Gender Bias in Self-Perception of Artificial Intelligence Knowledge, Impact, and Support Among Higher Education Students: An Observational Study. *ACM Transactions on Computing Education*, 25(2): 1-15.

Capp, M. J. (2017). The Effectiveness of Universal Design for Learning: A Meta-Analysis of Literature Between 2013 and 2016. *International Journal of Inclusive Education*, 21(8): 791-807.

Carolus, A., Koch, M. J., Straka, S., Latoschik, M. E., and Wienrich, C. (2023). MAILS-Meta AI Literacy Scale: Development and Testing of an AI Literacy Questionnaire Based on Well-Founded Competency Models and Psychological Change-and Meta-Competencies. *Computers in Human Behavior: Artificial Humans*, 1(2): 100014.

Chai, C. S., Yu, D., King, R. B., and Zhou, Y. (2024). Development and Validation of the Artificial Intelligence Learning Intention Scale (AILIS) for University Students. *SAGE Open*, 14(2): 1–16.

Chiu, T. K. F., Ahmad, Z., Ismailov, M., and Sanusi, I. T. (2024). What Are Artificial Intelligence Literacy and Competency? A Comprehensive Framework to Support Them. *Computers and Education Open*, 6: 100171.

Clarke, K. A. (2005). The Phantom Menace: Omitted Variable Bias in Econometric Research. *Conflict Management and Peace Science*, 22(4): 341–352.

Crawford, K. (2021). *Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence*. New Haven, Connecticut: Yale University Press.

DeVellis, R. F. (2003). *Scale Development: Theory and Applications (2nd ed.)*. Newbury Park: Sage Publications.

Drydakis, N. (2015). Economics Applicants in the UK Labour Market: Entry Standards, University Reputation and Employment Outcomes. *International Journal of Manpower*, 36(3): 296-333.

Drydakis, N. (2016). The Effect of University Attended on Graduates' Labour Market Prospects: A Field Study of Great Britain. *Economics of Education Review*, 52: 192-208.

Drydakis, N. (2022). Artificial Intelligence and Reduced SMEs' Business Risks. A Dynamic Capabilities Analysis During the COVID-19 Pandemic. *Information Systems Frontiers*, 24: 1223–1247.

Drydakis, N. (2024a). Artificial Intelligence Capital and Employment Prospects. *Oxford Economic Papers*, 76(4): 901-919.

Drydakis, N. (2024b). Reducing the Gender Digital Divide Amongst Immigrant Entrepreneurs, in G. Meramveliotakis and M. Manioudis (Eds). *Sustainable Economic Development Perspectives from Political Economy and Economics Pluralism* (pp. 237-264). London: Routledge.

Drydakis, N. (2025a). *Artificial Intelligence and Labor Market Outcomes*. IZA World of Labor: 514.

Drydakis, N. (2025b). Small Enterprises' Digital Competencies and Financial Performance, in V. Aranitou, A. Angelakis, and M. Manioudis (Eds), *The Economic Impact of Small and Medium-Sized Enterprises Analytical Approaches to Growth and Innovation Challenges Amid Crises in Europe* (pp. 55-68). London: Palgrave Macmillan.

Echeberria, L. (2022). *Artificial Intelligence for Business*. London: Springer International Publishing.

Hodgson, G.M. (2014). What is Capital? Economists and Sociologists Have Changed its Meaning: Should it Be Changed Back? *Cambridge Journal of Economics*, 38(5): 1063–86.
Hornberger, M., Bewersdorff, A., and Nerdel, C. (2023). What Do university Students Know About Artificial Intelligence? Development and Validation of an AI Literacy Test. *Computers and Education: Artificial Intelligence*, 5: 100165.
Hu, L. T., and Bentler, P. M. (1999). Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1): 1-55.
Ignatow, G., and Robinson, L. (2017). Pierre Bourdieu: Theorizing the Digital. *Information Communication and Society*, 20(7): 950–966.
Intahchomphoo, C., and Gundersen, O. E. (2020). Artificial Intelligence and Race: A Systematic Review. *Legal Information Management*, 20(2): 74-84.
Kolb, D. A. (1984). *Experiential Learning: Experience as the Source of Learning and Development*. Hoboken, New Jersey: Prentice Hall.
Kong, S.-C., Cheung, W. M.-Y., and Zhang, G. (2021). Evaluation of An Artificial Intelligence Literacy Course for University Students with Diverse Study Backgrounds. *Computers and Education: Artificial Intelligence*, 2: 100026.
Kong, S.-C., Cheung, W. M.-Y., and Zhang, G. (2022). Evaluating Artificial Intelligence Literacy Courses for Fostering Conceptual Learning, Literacy and Empowerment in University Students: Refocusing to Conceptual Building. *Computers in Human Behavior Reports*, 7: 100223.
Kong, S.-C., Cheung, W. M.-Y., and Zhang, G. (2023). Evaluating an Artificial Intelligence Literacy Programme for Developing University Students' Conceptual Understanding, Literacy, Empowerment and Ethical Awareness. *Educational Technology and Society*, 26(1): 16-30.
Laupichler, C. A., Aster, A., Schirch, J., and Raupach, T. (2022). Artificial Intelligence Literacy in Higher and Adult Education: A Scoping Literature Review. *Computers and Education: Artificial Intelligence*, 3: 100101.
Long, D., and Magerko, B. (2020). What is AI Literacy? Competencies and Design Considerations. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (pp. 1–16). https://doi.org/10.1145/3313831.3376727.
Mishra, P., and Koehler, M. J. (2006). Technological Pedagogical Content Knowledge: A Framework for Teacher Knowledge. *Teachers College Record*, 108(6): 1017–1054.
Munoz, J. M., and Naqvi, A. (2018). *Business Strategy in the Artificial Intelligence Economy*. Hampton, New Jersey: Business Expert Press.
Noble, S. U. (2018). *Algorithms of Oppression: How Search Engines Reinforce Racism*. N.Y.: New York University Press.
Piaget, J. (1952). *The Origins of Intelligence in Children*. N.Y.: International Universities Press.
Russell, S. J., and Norvig, P. (2022). Artificial Intelligence: A Modern Approach (4th ed., global edition). London: Pearson.
Sen, A. (1997). Human Capital and Capabilities. *World Economies*, 25(12): 1959–1961.
Singh, E., Vasishta, P., and Singla, A. (2025). AI-Enhanced Education: Exploring the Impact of AI Literacy on Generation Z's Academic Performance in Northern India. *Quality Assurance in Education*, 33(2): 185-202.
Sollosy, M., and McInerney, M. (2022). Artificial Intelligence and Business Education: What Should be Taught. *The International Journal of Management Education*, 20: 100720.
Spence, M. (1973). Job Market Signaling. The Quarterly Journal of Economics, 87(3): 355–374.
Vaisey, S. and Miles, A. (2017). What You Can—And Can't—Do With Three-Wave Panel Data. *Sociological Methods and Research*, 46(1): 44-67.
Vygotsky, L. S. (1978). *Mind in Society: The Development of Higher Psychological Processes*. Cambridge, M.A.: Harvard University Press.
Wang, S., Sun, Z., and Chen, Y. (2023). Effects of Higher Education Institutes' Artificial Intelligence Capability on Students' Self-Efficacy, Creativity, and Learning Performance. *Education and Information Technologies*, 28: 4919–4939.

Zahid, G., Batool, N., Riaz, M.A., Islam, R., Yaqoob, L., Rizwan, S., Gulfam, R. and Islam, I. (2025). Attitude Towards Artificial Intelligence as Predictor of Artificial Intelligence Literacy and Academic Achievement Among University Students. *International Journal of Social Sciences Bulletin*, 3(1): 139-146.

Table 1. Descriptive statistics		
	Panel I. Mean (Std. Dev.)	**Panel II. Observations**
Men (%)	69.16 (0.46)	n=120
White individuals (%)	75.83 (0.42)	n=120
Distinction in Mathematics (%)	32.50 (0.46)	n=120
Distinction in Empirical methods (^) (%)	34.16 (0.47)	n=120
Distinction in Economics (^^) (%)	29.16 (0.45)	n=120
AI Capital of Students scale (c.)	75.91 (26.54)	n=240
AI Capital test scores (^^^) (c.)	39.86 (18.98)	n=240
Grades in AI in Business Environments module (c.)	54.77 (14.68)	n=120
Awarded a distinction in degree classification (%)	27.50 (0.44)	n=120
Success rate in AI in Business Environments module (%)	100.00 (0.00)	n=120
Employed six months after graduation (%)	44.16 (0.49)	n=120
Unemployed six months after graduation (%)	14.16 (0.35)	n=120
Economically inactive six months after graduation (%)	41.66 (0.49)	n=120

Notes: The dataset covers the years 2023, and 2024. (^) Average of Statistics and Econometrics grades. (^^) Average of Microeconomics and Macroeconomics grades. (^^^) AI Capital was assessed through a 120-question test. (c.) Continuous variable.

Table 2. Tabulation analysis. Mean (Std. Dev.)

	Panel I. AI Capital of Students scale (c.)	**Panel II. AI Capital test scores (#) (c.)**	**Panel III. Grades in AI in Business Environments module (c.)**
Before training (^)	53.70 (11.07) n=120	25.68 (13.49) n=120	-
After training (^^)	98.12 (17.23) n=120	54.04 (11.68) n=120	-
t-test	t=23.75***	t=17.40***	-
Men	79.78 (27.34) n=166	43.22 (18.51) n=166	58.60 (15.38) n=83
Women	67.22 (22.49) n=74	32.31 (17.93) n=74	46.18 (8.01) n=37
t-test	t=3.46***	t=4.25***	t=4.62***
White individuals	79.71 (26.87) n=182	43.31 (18.43) n=182	58.31 (15.14) n=91
Non-White individuals	63.98 (21.67) n=58	29.01 (16.58) n=58	43.65 (3.18) n=29
t-test	t=4.05***	t=5.26***	t=5.16***
Distinction in Mathematics	88.41 (28.86) n=78	51.10 (17.36) n=78	68.66 (15.64) n=39
No distinction in Mathematics	69.89 (23.13) n=162	34.45 (17.33) n=162	48.08 (8.06) n=81
t-test	t=5.34***	t=6.96***	t=9.52***
Distinction in Empirical methods (^^^)	87.43 (28.77) n=82	48.97 (18.90) n=82	67.04 (16.13) n=41
No distinction in Empirical methods (^^^)	69.93 (23.23) n=158	35.13 (17.27) n=158	48.40 (8.66) n=79
t-test	t=5.09***	t=5.69***	t=8.24***
Distinction in Economics (^^^^)	87.97 (28.56) n=70	51.05 (18.01) n=70	69.02 (16.20) n=35
No distinction in Economics (^^^^)	70.94 (24.04) n=170	35.25 (17.44) n=170	48.90 (8.92) n=85
t-test	t=4.71***	t=6.32***	t=8.70***
Employed individuals	108.67 (18.32) n=53	63.83 (10.12) n=53	66.84 (13.97) n=53
Unemployed or economically inactive individuals	89.77 (10.53) n=67	46.29 (5.25) n=67	45.22 (5.02) n=67
t-test	t=7.09***	t=12.24***	t=11.75***

Notes. The dataset covers the years 2023, and 2024. (c.) Continuous variable. (^) Indicates the period before the AI in Business Environments module. (^^) Indicates the period after the AI in Business Environments module. (^^^) Average of Statistics and Econometrics grades. (^^^^) Average of Microeconomics and Macroeconomics grades. (#) AI Capital was assessed through a 120-question test. (***) Statistically significant at the 1% level.

Table 3. Correlation matrix

	AI Capital of Students scale	**AI Capital of Students scale: Knowledge**	**AI Capital of Students scale: Skills**	**AI Capital of Students scale: Capabilities**	**AI Capital test scores** (^)	**After training** (^^)	**Men**	**White individuals**	**Distinction in Mathematics**	**Distinction in Empirical methods** (^^^)	**Distinction in Economics** (^^^^)	**Grades in AI in Business Environments module**	**Employed individuals** (#)
AI Capital of Students scale	1												
AI Capital of Students scale: Knowledge	0.989 (0.000)***	1											
AI Capital of Students scale: Skills	0.949 (0.000)***	0.917 (0.000)***	1										
AI Capital of Students scale: Capabilities	0.970 (0.000)***	0.934 (0.000)***	0.904 (0.000)***	1									
AI Capital test scores (^)	0.919 (0.000)***	0.921 (0.000)***	0.841 (0.000)***	0.889 (0.000)***	1								
After training (^^)	0.836 (0.000)***	0.801 (0.000)***	0.799 (0.000)***	0.866 (0.000)***	0.748 (0.000)***	1							
Men	0.218 (0.000)***	0.233 (0.000)***	0.187 (0.000)***	0.191 (0.002)***	0.266 (0.000)***	0.000 (1.000)	1						
White individuals	0.254 (0.000)***	0.268 (0.000)***	0.246 (0.000)***	0.210 (0.001)***	0.323 (0.000)***	0.000 (1.000)	0.550 (0.000)***	1					
Distinction in Mathematics	0.327 (0.000)***	0.360 (0.000)***	0.299 (0.000)***	0.254 (0.000)***	0.411 (0.000)***	-0.000 (1.000)	0.078 (0.228)	0.267 (0.000)***	1				
Distinction in Empirical methods (^^^)	0.313 (0.000)***	0.340 (0.000)***	0.272 (0.000)***	0.260 (0.000)***	0.346 (0.000)***	-0.000 (1.000)	0.214 (0.000)***	0.205 (0.000)***	0.625 (0.000)***	1			
Distinction in Economics (^^^^)	0.291 (0.000)***	0.323 (0.000)***	0.235 (0.000)***	0.241 (0.000)***	0.379 (0.000)***	-0.000 (1.000)	0.031 (0.628)	0.105 (0.000)***	0.572 (0.000)***	0.542 (0.000)***	1		
Grades in AI in Business Environments module	0.762 (0.000)***	0.765 (0.000)***	0.628 (0.000)***	0.665 (0.000)***	0.915 (0.000)***	-	0.329 (0.000)***	0.429 (0.000)***	0.659 (0.000)***	0.604 (0.000)***	0.625 (0.000)***	1	
Employed individuals (#)	0.546 (0.000)***	0.541 (0.000)***	0.428 (0.000)***	0.513 (0.000)***	0.748 (0.000)***	-	0.303 (0.000)***	0.384 (0.000)***	0.457 (0.000)***	0.420 (0.000)***	0.463 (0.000)***	0.734 (0.000)***	1

Notes: The dataset covers the years 2023, and 2024. (^) AI Capital was assessed through a 120-question test. (^^) Indicates the period after the AI in Business Environments module. (^^^) Average of Statistics and Econometrics grades. (^^^^) Average of Microeconomics and Macroeconomics grades. (#) The reference category is individuals who are unemployed or economically inactive. (***) Statistically significant at the 1% level.

Table 4. Regression outcomes

	Model I Pooled OLS. AI Capital of Students scale	Model II Random Effects. AI Capital of Students scale	Model III Fixed Effects. AI Capital of Students scale	Model IV Pooled OLS. AI Capital test scores (#)	Model V Random effects. AI Capital test scores (#)	Model VI Fixed Effects. AI Capital test scores (#)	Model VII OLS. Grades in AI in Business Environments module	Model VIII OLS. Grades in AI in Business Environments module
After training (^)	44.425 (1.217)***	44.425 (0.917)***	44.425 (0.917)***	28.358 (0.996)***	28.358 (0.488)***	28.358 (0.488)***	-	-
Men	6.675 (1.637)***	6.675 (1.981)***	-	6.177 (1.340)***	6.177 (1.805)***	-	7.672 (2.112)***	5.087 (2.013)**
White individuals	7.172 (1.790)***	7.172 (2.166)***	-	6.485 (1.465)***	6.485 (1.974)***	-	4.779 (2.309)**	2.439 (2.175)
Distinction in Mathematics	8.144 (1.861)***	8.144 (2.252)***	-	8.925 (1.523)***	8.925 (2.052)***	-	9.871 (2.401)***	7.117 (2.278)***
Distinction in Empirical methods (^^)	5.333 (1.772)***	5.333 (2.144)**	-	0.997 (1.450)	0.997 (1.954)	-	10.550 (2.271)***	7.535 (2.179)***
Distinction in Economics (^^^)	8.031 (1.760)***	8.031 (2.130)***	-	8.163 (1.441)***	8.163 (1.941)***	-	3.916 (2.287)*	1.865 (2.141)
AI Capital of Students scale (^^^^)	-	-	-	-	-	-	-	0.302 (0.064)***
F	184.70	-	2344.39	135.09	-	3370.09	29.43	33.58
Prob>F	0.000	-	0.000	0.000	-	0.000	0.000	0.000
R-squared	0.873	-	0.703	0.834	-	0.559	0.679	0.733
Wald chi2	-	2570.89	-	-	3594.00	-	-	-
Prob>chi2	-	0.000	-	-	0.000	-	-	-
R-squared	-	0.875	-	-	0.840	-	-	-
Breusch and Pagan Lagrangian multiplier test	chibar2=20.43 p<0.01			chibar2=67.76 p<0.01			-	-
Hausman test	chi2=0.01 p>0.10			chi2=0.01 p>0.10			-	-
Observations	240	240	240	240	240	240	120	120

Notes: The dataset covers the years 2023, and 2024. (^) Indicates the period after the AI in Business Environments module. (^^) Average of Statistics and Econometrics grades. (^^^) Average of Microeconomics and Macroeconomics grades. (^^^^) This variable indicates the level of AI Capital of Students scale after completing the AI in Business Environments module. Pooled OLS and Random Effects models control for cohort deliveries. (#) AI Capital was assessed through a 120-question test. (***) Statistically significant at the 1% level. (**) Statistically significant at the 5% level. (*) Statistically significant at the 10% level.

Table 5. Regression outcomes

	Model I	**Model II**	**Model III**
	Random Effects. AI Capital of Students scale: Knowledge	**Random Effects. AI Capital of Students scale: Skills**	**Random Effects. AI Capital of Students scale: Capabilities**
After training (^)	23.558 (0.585)***	7.508 (0.278)***	13.358 (0.294)***
Men	4.110 (1.209)***	0.811 (0.411)**	1.743 (0.573)***
White individuals	3.974 (1.322)***	1.487 (0.450)***	1.714 (0.626)***
Distinction in Mathematics	5.171 (1.375)***	1.524 (0.468)***	1.436 (0.651)**
Distinction in Empirical methods (^^)	3.031 (1.309)**	0.834 (0.445)*	1.463 (0.620)**
Distinction in Economics (^^^)	5.065 (1.300)***	0.940 (0.442)**	2.010 (0.616)***
Wald chi2	1840.79	858.28	2209.15
Prob>chi2	0.000	0.000	0.000
R-squared	0.849	0.777	0.871
Observations	240	240	240

Notes: The dataset covers the years 2023, and 2024. (^) Indicates the period after the AI in Business Environments module. (^^) Average of Statistics and Econometrics grades. (^^^) Average of Microeconomics and Macroeconomics grades. All models control for cohort deliveries. (***) Statistically significant at the 1% level. (**) Statistically significant at the 5% level. (*) Statistically significant at the 10% level.

Table 6. Regression outcomes

	Model I	**Model II**	**Model III**	**Model IV**
	Random Effects. AI Capital of Students scale: Men	**Random Effects. AI Capital of Students scale: Women**	**Random Effects. AI Capital of Students scale: White individuals**	**Random Effects. AI Capital of Students scale: Non-White individuals**
After training (^)	45.975 (1.144)***	40.945 (1.357)***	45.538 (1.091)***	40.931 (1.487)***
Men	-	-	10.420 (2.381)***	-1.025 (2.168)
White individuals	13.205 (3.386)***	5.079 (2.275)***	-	-
Distinction in Mathematics	9.485 (2.914)***	3.816 (2.720)	9.817 (2.381)***	-4.087 (4.236)
Distinction in Empirical methods (^^)	5.368 (2.659)**	4.312 (3.046)	4.475 (2.485)*	7.398 (2.800)***
Distinction in Economics (^^^)	9.508 (2.736)***	5.304 (2.646)**	10.064 (2.429)***	5.509 (2.800)**
Wald chi2	1760.23	954.67	1899.47	775.91
Prob>chi2	0.000	0.000	0.000	0.000
R-squared	0.878	0.916	0.880	0.935
Observations	166	74	182	58

Notes: The dataset covers the years 2023, and 2024. (^) Indicates the period after the AI in Business Environments module. (^^) Average of Statistics and Econometrics grades. (^^^) Average of Microeconomics and Macroeconomics grades. All models control for cohort deliveries. (***) Statistically significant at the 1% level. (**) Statistically significant at the 5% level. (*) Statistically significant at the 10% level.

Table 7. Regression outcomes

	Model I	**Model II**	**Model III**
	Probit. Employment (#)	**Probit. Employment** (#)	**Probit. Employment** (#)
AI Capital of Students scale	0.013 (0.005)**	-	-
AI Capital test scores (^)	-	0.053 (0.010)***	-
Grades in AI in Business Environments module	-	-	0.057 (0.011)***
Men	0.064 (0.146)	-0.105 (0.187)	-0.106 (0.178)
White individuals	0.392 (0.129)**	0.221 (0.189)	0.195 (0.212)
A distinction in the degree classification	0.408 (0.144)**	0.046 (0.209)	-0.051 (0.235)
LR chi2	66.36	95.54	100.07
Prob>chi2	0.000	0.000	0.000
Pseudo R2	0.402	0.580	0.607
Observations	120	120	120

Notes: The dataset covers the years 2023, and 2024. (^) AI Capital was assessed through a 120-question test. (#) The marginal effects from Probit models are presented. The reference category comprises students who are either unemployed or economically inactive. (***) Statistically significant at the 1% level. (**) Statistically significant at the 5% level.

Appendix.

Table A.I. AI Capital of Students scale: Mean (Std. Dev.)			
Scale items (SI)	**Panel I. Before training**	**Panel II. After training**	**t-test**
Theme A. Knowledge			
Fundamental Concepts of AI			
SI1. I understand the differences between AI, machine learning, deep learning, and automation (e.g. their distinct scopes, applications, and underlying technologies).	1.375 (0.661)	2.350 (0.784)	t=10.41
SI2. I understand core AI concepts, including model training (e.g., model optimisation, data representation).	1.625 (0.710)	2.541 (0.868)	t=8.94
SI3. I understand the differences between supervised and unsupervised learning (e.g., labelled data vs unlabelled data).	1.508 (0.850)	2.616 (0.954)	t=9.49
Data and Analytics in AI			
SI4. I understand the role of big data in AI applications (e.g., data volume, variety, and velocity in AI systems).	1.358 (0.683)	2.558 (0.950)	t=11.23
SI5. I understand techniques in predictive analytics (e.g., forecasting, trend analysis)	1.483 (0.733)	2.475 (0.943)	t=9.09
SI6. I understand natural language processing techniques (e.g., tokenisation, sentiment analysis, named entity recognition).	1.425 (0.721)	2.700 (0.975)	t=11.51
SI7. I understand reinforcement learning techniques (e.g., Q-learning, policy gradients).	1.425 (0.816)	2.608 (0.955)	t=10.31
SI8. I understand neural network techniques (e.g., convolutional neural networks, recurrent neural networks).	1.400 (0.726)	2.516 (0.943)	t=10.27
SI9. I understand data-driven decision-making processes in AI (e.g., data collection, processing, and analysis to inform AI models).	1.300 (0.629)	2.416 (0.940)	t=10.80
AI Infrastructure and Tools			
SI10. I understand AI tools and frameworks for model building and deployment (e.g., TensorFlow, PyTorch, scikit-learn, and Keras).	1.391 (0.598)	2.491 (0.888)	t=11.25
SI11. I understand the role of cloud platforms (e.g., AWS, Google Cloud) in supporting AI projects (e.g., scalability, remote access, and computational resources).	1.316 (0.564)	2.441 (0.968)	t=11.00
SI12. I understand the importance of data storage and management (e.g., scalability, security, organisation) in AI projects.	1.358 (0.719)	2.508 (0.943)	t=10.62
Bias and Fairness in AI			
SI13. I understand the sources of bias in AI models and data, including selection and confirmation bias (e.g., biased training data, algorithmic bias).	1.325 (0.552)	2.616 (0.971)	t=12.66
SI14. I understand the impact of biased data on AI outcomes (e.g., discrimination, inaccurate predictions).	1.325 (0.650)	2.466 (0.888)	t=11.35
SI15. I understand techniques to mitigate bias and improve fairness in AI models (e.g., fairness constraints, data balancing).	1.366 (0.533)	2.391 (0.946)	t=10.34
Ethical and Legal Considerations			
SI16. I understand the ethical issues, including data ethics, in AI (e.g., biases in decision-making, misuse of personal data).	1.283 (0.552)	2.508 (1.137)	t=10.61
SI17. I understand the legal considerations involved in the use of AI in business (e.g., compliance with regulations, intellectual property).	1.408 (0.601)	2.566 (0.959)	t=11.20
SI18. I understand the privacy concerns related to AI data usage (e.g., data protection, consent).	1.291 (0.640)	2.541 (0.942)	t=12.02
Human-AI Interaction			
SI19. I understand the design of AI systems that work effectively alongside human users (e.g., user interface design, user feedback)	1.275 (0.533)	2.425 (0.975)	t=11.33
SI20. I understand interpretable AI and its importance for building trust in AI systems (e.g., transparency in AI decision-making).	1.383 (0.624)	2.458 (0.951)	t=10.35
AI in Emerging Technologies			
SI21. I understand the role of AI in emerging technologies, such as the Internet of Things (IoT) and autonomous systems (e.g., smart devices).	1.325 (0.537)	2.358 (0.968)	t=10.22
Theme B. Skills			
Data Preparation and Analysis			
SI22. I have prepared and cleaned data (e.g., handling missing data, normalisation, feature engineering) using AI tools to ensure data quality and derive actionable insights.	1.300 (0.495)	2.275 (0.897)	t=10.42
SI23. I have applied statistical and multivariate methods, such as regression analysis, to interpret data trends using AI-related tools (e.g., Python, R).	1.216 (0.433)	2.266 (0.976)	t=10.77
Programming Proficiency			
SI24. I have used programming languages commonly used in AI, such as Python and R, to develop and implement models (e.g., coding, debugging, model training).	1.208 (0.483)	2.383 (0.881)	t=12.81
AI Model Development and Evaluation			

SI25. I have built AI models to analyse business data and assess their performance using metrics such as accuracy, precision, recall, and F1 score (e.g., classification tasks, predictive models).	1.333 (0.598)	2.300 (0.922)	t=9.63
SI26. I have identified and addressed overfitting and underfitting using AI related methods such as cross-validation and regularisation (e.g., dropout layers in neural networks, L2 regularisation, k-fold validation).	1.208 (0.465)	2.350 (0.904)	t=12.30
SI27. I have run simulations with AI tools for scenario analysis (e.g., A/B testing, sensitivity analysis).	1.325 (0.504)	2.475 (0.916)	t=12.04
AI Implementation and Deployment			
SI28. I have used AI-based tools to automate routine business processes, such as data entry and report generation (e.g., robotic process automation for data entry, natural language processing for automated customer service responses).	1.258 (0.557)	2.308 (0.923)	t=10.66
Theme C. Capabilities			
Identifying AI Opportunities			
SI29. I can identify areas in business operations where AI could enhance performance (e.g., process optimisation, customer service improvement).	1.275 (0.533)	2.241 (0.840)	t=10.63
Communication of AI-Driven Solutions			
SI30. I can explain the potential benefits and limitations of AI in business environments (e.g., risk assessment, cost reduction, accuracy improvement).	1.200 (0.441)	2.116 (0.811)	t=10.86
SI31. I can propose AI-driven solutions to address specific business challenges, such as customer service improvement (e.g., chatbots, predictive analytics for customer needs).	1.366 (0.548)	2.375 (0.820)	t=11.20
Leveraging AI for Competitive Advantage			
IS32. I can leverage AI to create competitive advantages, such as personalised customer experiences (e.g., recommendation systems, targeted marketing).	1.208 (0.447)	2.308 (0.828)	t=12.80
AI Applications			
SI33. I can use AI applications for financial forecasting to support sustainable outcomes (e.g., revenue prediction, expense optimisation).	1.225 (0.475)	2.475 (0.916)	t=13.27
SI34. I can use AI for customer segmentation and targeted marketing to increase market share (e.g., clustering, personalised campaigns).	1.325 (0.567)	2.391 (0.937)	t=10.66
Innovation and Data Governance			
SI35. I can propose innovation strategies by promoting data-driven initiatives through AI (e.g., product development, operational efficiency).	1.341 (0.586)	2.366 (0.934)	t=10.18
Change Management and Implementation			
SI36. I can manage the integration of AI systems into existing business processes, ensuring minimal disruption and maximum value (e.g., staff training, process re-engineering).	1.333 (0.598)	2.491 (0.916)	t=11.59
SI37. I can establish metrics and implement feedback loops to monitor and enhance the performance of AI systems (e.g., model accuracy, response time).	1.366 (0.593)	2.475 (0.839)	t=11.82
Risk Management			
SI38. I can identify potential risks associated with AI implementation, such as data privacy issues and system failures (e.g., security breaches, data misuse).	1.408 (0.614)	2.716 (0.861)	t=13.54
SI39. I can develop strategies to mitigate identified AI-related risks, ensuring secure and ethical AI deployment (e.g., encryption, regular audits).	1.450 (0.646)	2.591 (0.948)	t=10.89
Cross-Functional Collaboration and Stakeholder Management			
SI40. I can collaborate with personnel such as IT, marketing, and operations teams to ensure cohesive AI integration (e.g., data sharing, project coordination, requirement gathering).	1.341 (0.614)	2.650 (0.984)	t=12.36
Observations	120	120	

Notes: Each question is answered using a five-point Likert scale, ranging from 'totally disagree' to 'totally agree'. All differences are significant at the 1% level.

Appendix

Table A.II. Learning objectives and applied learning developments for the module AI in Business Environments

Panel I: Scale items^	Panel II. Learning objectives	Panel III. Applied learning developments
Theme A. Knowledge		
Fundamental Concepts of AI		
SI1.	LO1. Understand the differences between AI, machine learning, deep learning, and automation.	ALD1. Development of concept differentiation, critical thinking, digital literacy, technical terminology use, and understanding of AI categories
SI2.	LO2. Understand core AI concepts, including model training.	ALD2. Development of understanding of the AI pipeline, including modelling, algorithmic comprehension, conceptual reasoning, and fluency in core AI functions.
SI3.	LO3. Understand the differences between supervised and unsupervised learning.	ALD3. Development of classification and clustering knowledge, analytical reasoning, model selection, applied statistics, and data interpretation.
Data and Analytics in AI		
SI4.	LO4. Understand the role of big data in AI applications.	ALD4. Development of big data awareness, data handling proficiency, contextual application, analytical thinking, and scalability understanding.
SI5.	LO5. Understand techniques in predictive analytics.	ALD5. Development of forecasting techniques, quantitative analysis, trend interpretation, insight generation, and model training.
SI6.	LO6. Understand natural language processing techniques.	ALD6. Development of natural language processing, linguistic analysis, text data handling, semantic interpretation, and the use of AI tools.
SI7.	LO7. Understand reinforcement learning techniques.	ALD7. Development of reinforcement learning knowledge, sequential decision-making, adaptability, simulation techniques, and algorithm dynamics.
SI8.	LO8. Understand neural network techniques.	ALD8. Development of understanding of neural architectures, deep learning techniques, pattern recognition, layer configuration, and backpropagation.
SI9.	LO9. Understand data-driven decision-making processes in AI.	ALD9. Development of evidence-based reasoning, strategic thinking, data evaluation, logical decision-making, and application of AI to business processes.
AI Infrastructure and Tools		
SI10.	LO10. Understand AI tools and frameworks for model building and deployment.	ALD10. Development of familiarity with AI tools, framework usage, model deployment, technology fluency, and prototyping abilities.
SI11.	LO11. Understand the role of cloud platforms.	ALD11. Development of cloud computing literacy, platform integration, understanding of distributed systems, data scalability, and cloud architecture.
SI12.	LO12. Understand the importance of data storage and management in AI projects.	ALD12. Development of database management, information organisation, data lifecycle knowledge, storage system understanding, and data security practices.
Bias and Fairness in AI		
SI13.	LO13. Understand sources of bias in AI models and data, including selection and confirmation bias.	ALD13. Development of bias detection, ethical awareness, fairness analysis, system auditing, and critical evaluation of datasets and models.
SI14.	LO14. Understand the impact of biased data on AI outcomes.	ALD14. Development of impact assessment, ethical reasoning, model critique, understanding of data influence, and evaluation of AI outcomes.
SI15.	LO15. Understand techniques to mitigate bias and improve fairness in AI models.	ALD15. Development of techniques for bias mitigation, ethical model design, fair AI application, and inclusive development strategies.
Ethical and Legal Considerations		
SI16.	LO16. Understand ethical issues, including data ethics, in AI.	ALD16. Development of ethical awareness, responsible innovation, data governance understanding, societal impact evaluation, and moral reasoning.
SI17.	LO17. Understand legal considerations for AI use in business.	ALD17. Development of regulatory literacy, legal risk assessment, compliance knowledge, governance alignment, and understanding of legal frameworks.
SI18.	LO18. Understand privacy concerns related to AI data usage.	ALD18. Development of privacy awareness, data protection practices, consent handling, ethical reasoning, and risk management related to data use.
Human-AI Interaction		
SI19.	LO19. Understand the design of AI that works effectively alongside human users.	ALD19. Development of user-centred design, human-AI collaboration, ergonomics in system design, task optimisation, and operational alignment.
SI20.	LO20. Understand interpretable AI and its importance in building trust in AI systems.	ALD20. Development of approaches to transparency, model interpretability, trust-building, system accountability, and explanation of AI processes.
AI in Emerging Technologies		
SI21.	LO21. Understand the role of AI in emerging technologies, such as the Internet of Things (IoT) and autonomous systems.	ALD21. Development of technological foresight, digital transformation understanding, system integration strategies, and strategic innovation.
Theme B. Skills		

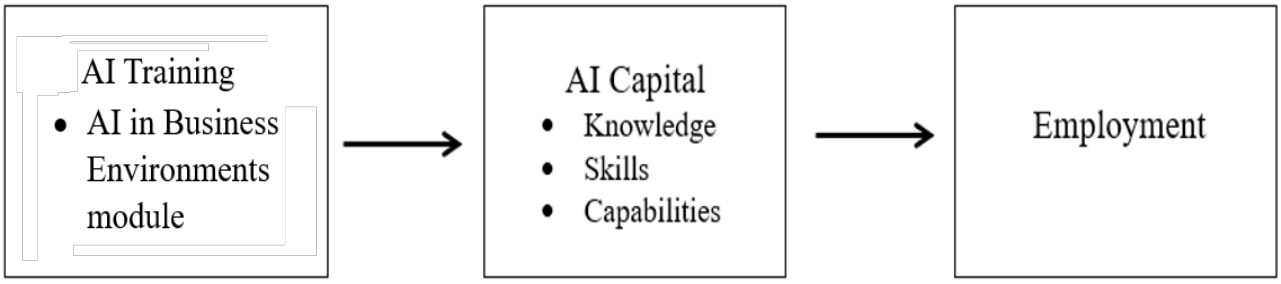
Data Preparation and Analysis		
SI22.	LO22. Prepare and clean data using AI tools to ensure data quality and derive actionable insights.	ALD22. Development of data wrangling techniques, cleaning skills, AI tool proficiency, insight generation, and data quality assurance.
SI23.	LO23. Apply statistical and multivariate methods, such as regression analysis, to interpret data trends using AI-related tools.	ALD23. Development of statistical analysis, trend interpretation, regression skills, quantitative reasoning, and data modelling using AI tools.
Programming Proficiency		
SI24.	LO24. Use programming languages commonly used in AI, such as Python and R, to develop and implement models.	ALD24. Development of programming proficiency in Python and R, coding fluency, model scripting, technical problem-solving, and AI implementation.
AI Model Development and Evaluation		
SI25.	LO25. Build AI models to analyse business data and assess their performance using metrics such as accuracy, precision, recall, and F1 score.	ALD25. Development of skills in AI model building, performance evaluation, metric interpretation, business analytics, and decision support.
SI26.	LO26. Identify and address overfitting and underfitting using AI-related methods such as cross-validation and regularisation.	ALD26. Development of model tuning, overfitting/underfitting identification, cross-validation application, and performance optimisation.
SI27.	LO27. Run simulations with AI tools for scenario analysis.	ALD27. Development of scenario analysis, simulation running, forecasting, risk modelling, and outcome visualisation using AI tools.
AI Implementation and Deployment		
SI28.	LO28. Use AI-based tools to automate routine business processes, such as data entry and report generation.	ALD28. Development of automation design, workflow improvement, operational streamlining, routine task reduction, and tool configuration.
Theme C. Capabilities		
Identifying AI Opportunities		
SI29.	LO29. Identify areas in business operations where AI could enhance performance.	ALD29. Development of strategic insight, business process analysis, innovation identification, performance enhancement ideas, and AI opportunity mapping.
Communication of AI-Driven Solutions		
SI30.	LO30. Explain the potential benefits and limitations of AI in business environments.	ALD30. Development of communication, stakeholder engagement, benefit–risk articulation, persuasive reasoning, and conceptual explanation.
SI31.	LO31. Propose AI-driven solutions to address specific business challenges, such as customer service improvement.	ALD31. Development of solution generation, problem-solving, AI system design, business alignment, and innovation planning.
Leveraging AI for Competitive Advantage		
SI32.	LO32. Leverage AI to create competitive advantages, such as personalised customer experiences.	ALD32. Development of strategic use of AI, customer insight generation, competitive analysis, deployment for personalisation, and differentiation tactics.
AI Applications		
SI33.	LO33. Use AI applications for financial forecasting to secure sustainable outcomes.	ALD33. Development of financial forecasting techniques, sustainability planning, market analysis, predictive modelling, and outcome estimation.
SI34.	LO34. Use AI for customer segmentation and targeted marketing to increase market share.	ALD34. Development of customer segmentation strategies, targeted marketing, data-driven promotional planning, and market share analysis.
Innovation and Data Governance		
SI35.	LO35. Propose innovation strategies by promoting data-driven initiatives through AI.	ALD35. Development of innovation planning, AI strategy, data culture promotion, initiative leadership, and transformation enablement.
Change Management and Implementation		
SI36.	LO36. Manage the integration of AI systems into existing business processes, ensuring minimal disruption and maximum value.	ALD36. Development of change management, process integration, project coordination, disruption minimisation, and stakeholder communication.
SI37.	LO37. Establish metrics and implement feedback loops to monitor and enhance the performance of AI systems.	ALD37. Development of goal setting, feedback loop creation, performance tracking, system monitoring, and continuous improvement strategies.
Risk Management		
SI38.	LO38. Identify potential risks associated with AI implementation, such as data privacy issues and system failures.	ALD38. Development of risk identification, awareness of system vulnerabilities, data privacy considerations, and ethical hazard forecasting.
SI39.	LO39. Develop strategies to mitigate identified AI-related risks, ensuring secure and ethical AI deployment.	ALD39. Development of strategies to mitigate AI risks, contingency planning, secure deployment, policy design, and ethical safeguards.
Cross-Functional Collaboration and Stakeholder Management		
SI40.	LO40. Collaborate with personnel such as IT, marketing, and operations teams to ensure cohesive AI integration.	ALD40. Development of cross-functional collaboration, teamwork, stakeholder alignment, interdisciplinary communication, and shared project ownership.

Notes: (^) AI Capital of Students scale items.

Appendix

Table A.III. Scale Validation		
	Panel I. AI Capital of Students scale; All items	**Panel II. AI Capital of Students scale; Theme oriented**
Cronbach's Alpha (α) (All items: 40 items)	0.97	-
Cronbach's Alpha (α) (Theme A. Knowledge: 21 items)	-	0.95
Cronbach's Alpha (α) (Theme B. Skills: 7 items)	-	0.86
Cronbach's Alpha (α) (Theme C. Capabilities: 12 items)	-	0.90
H-test (H index) (All items: 40 items)	0.50	-
H-test (H index) (Theme A. Knowledge: 21 items)	-	0.50
H-test (H index) (Theme B. Skills: 7 items)	-	0.49
H-test (H index) (Theme C. Capabilities: 12 items)	-	0.47
Chi-squared to degrees of freedom ratio (chi2/df)	1.7	1.7
Root Mean Square Error of Approximation (RMSEA)	0.054	0.053
Standardised Root Mean Square Residual (SRMR)	0.041	0.040
Normed Fit Index (NFI)	0.807	0.808
Relative Noncentrality Index (RNI)	0.910	0.911
Comparative Fit Index (CFI)	0.910	0.911
Incremental Fit Index (IFI)	0.911	0.912
Notes: The dataset covers the years 2023, and 2024 (n=240).		

Figure 1. AI Learning–Capital–Employment Transition Model



Notes: This figure illustrates the AI Learning–Capital–Employment Transition model, which theorises the pathway from AI training, delivered through the AI in Business Environments module, to the development of AI Capital and improved employment outcomes. The module provides students with structured exposure to AI tools, concepts, and applications within business contexts. This pedagogical engagement fosters the accumulation of AI Capital, defined as a composite of knowledge, skills, and capabilities relevant to the understanding and strategic use of AI. In turn, these dimensions of AI Capital enhance students' employability by equipping them with competencies that are increasingly valued in AI-integrated workplaces.