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**Nick Drydakis**
*Anglia Ruskin University, University of Cambridge, GLO and IZA*

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**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

## Artificial Intelligence Capital and Employment Prospects

There is limited research assessing how AI knowledge affects employment prospects. The present study defines the term 'AI capital' as a vector of knowledge, skills and capabilities related to AI technologies, which could boost individuals' productivity, employment and earnings. Subsequently, the study reports the outcomes of a genuine correspondence test in England. It was found that university graduates with AI capital, obtained through an AI business module, experienced more invitations for job interviews than graduates without AI capital. Moreover, graduates with AI capital were invited to interviews for jobs that offered higher wages than those without AI capital. Furthermore, it was found that large firms exhibited a preference for job applicants with AI capital, resulting in increased interview invitations and opportunities for higher-paying positions. The outcomes hold for both men and women. The study concludes that AI capital might be rewarded in terms of employment prospects, especially in large firms.

**JEL Classification:** E24, I26, O14

**Keywords:** artificial intelligence, artificial intelligence capital, employment, wages, higher education, education

**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
United Kingdom

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

## 1. Introduction

Artificial intelligence (AI) involves the development of computer programs to complete tasks which would otherwise require human intelligence, such as problem solving and logical reasoning (Sollosy and McInerney, 2022). AI interprets external data and learns, then uses those learnings to achieve specific tasks via adaptation (Sollosy and McInerney, 2022). The impact of AI is similar to how automation changed many manufacturing processes (OECD, 2023; Sollosy and McInerney, 2022; Alekseeva et al., 2021). As such, AI has the potential to positively affect economic growth and to transform the economic landscape (OECD, 2023; Drydakis, 2022a). AI is increasingly impacting many aspects of business environments, including such areas as finance, marketing, management, human resources, and information technology, to name a few (OECD, 2023; Drydakis, 2022a). In the US, demand for AI skills in online job vacancy platforms quadrupled over the period from 2010 to 2019 (Alekseeva et al., 2021). Firms need a workforce who understand AI concepts and methods, are capable of using their knowledge and skills to manage an AI-augmented workplace, and are well-versed in collaborating with AI agents (Ransbotham et al., 2017).

The ability to understand, use, monitor, and critically reflect on AI tools without users necessarily being able to develop AI models themselves[1] – is perceived as a learning priority (Laupichler et al., 2022). Increasing AI skills among non-experts is considered as important as training AI experts, since the former group will most likely use AI or collaborate and coexist with it (Ng et al., 2021). Governments have recognized the need for AI learning programmes in schools, as well as higher and adult education (Laupichler et al., 2022). For instance, in 2021 the United Kingdom's government released the National AI Strategy, which aimed to boost business use of AI,

[1] AI tools are end-user products or applications that leverage AI technology to perform specific tasks. AI models, on the other hand, include the programming languages, frameworks and algorithms that enable the creation of AI tools.

attract international investment, and develop the next generation of technology talent (HM Government, 2021).

For employers to embrace and partner with AI technology, universities need to increasingly emphasize the development and maturation of their students' AI skills (Sollosy and McInerney, 2022). A few projects in recent years have introduced AI to university students from non-computer-science backgrounds, such as in business studies, education and medicine (Laupichler et al., 2022; Sollosy and McInerney, 2022). Universities can improve business education by preparing students to be professionals who understand business needs and can interpret the data analysis performed by AI, in order to provide data-informed decision making (Sollosy and McInerney, 2022).

Although policy makers highlight the need for educational programmes to address contemporary needs associated with AI skills (Laupichler et al., 2022; Sollosy and McInerney, 2022; Drydakis, 2022b), there is no empirical research available evaluating how AI knowledge affects employment prospects. The purpose of the present study is to fill this gap. In 2022, economics students studying in an English university completed a module on AI in business. Then, a correspondence test was performed to examine whether AI knowledge, which was obtained through the taught AI business module, could affect their employment prospects (Riach and Rich, 2002). Carefully matched, genuine job applications were forwarded in response to advertised job vacancies in ten occupations. The only difference between the applications was the level of AI knowledge. It is hypothesized that AI education forms graduates' AI knowledge, which might be socially valued and financially regarded in the labour market. The study assessed employers' recruitment behaviours in terms of access to vacancies, i.e. invitations to interviews, which also enabled the research to capture wage sorting.

There is ample theoretical and empirical evidence of the efficacy of education, training and skills to increase individuals' probability of employment and future earnings (Cahuc, Carcillo, and Zylberberg, 2014). This has long been part of the human capital theory, which proposes that individuals themselves have strong incentives to invest in education because they are the sole beneficiaries of their increased productivity (Becker, 1965). Notably, human capital theory has been extended by signalling models of education, to examine the ways in which education serves as a signal for productivity differences (Spence, 1973). Empirical evidence convincingly confirms that both human capital and signalling effects exist, and that both effects are observationally equivalent because better-educated and -trained individuals are more productive (Huntington-Klein, 2021).

The present study contributes to the literature in three ways. First, the study introduces the term 'AI capital', in a process that shapes a framework for capturing the educational gains related to AI. Given that AI knowledge is perceived to be socially, productively and economically valued, it is important to define a term that denotes individuals' level of AI capital, related to investments in AI education. AI capital could provide a conceptual framework enabling professionals to systematically assess a plethora of micro- and macro-oriented empirical questions, such as possible relations between AI capital and levels of employment and income.

Second, there is no empirical evidence on the relationship between AI knowledge obtained through training, and employment prospects for university students. However, there is a recognition that educators need to prepare students for the increasing pace of technological change brought about by the rapid advancements of AI technologies, and their introduction in the workplace (Xu and Babaian, 2021). Thus, the empirical assessments of this study might be of interest to policy makers and university faculties, by enabling them to observe AI knowledge payoffs for graduates' employability.

Third, the study adopts an experimental methodology, with the aim of minimizing unobserved heterogeneities that would themselves affect subsequent outcomes in the labour market. A large part of the empirical work in the economics of education concerns estimates of education's causal effect on employment outcomes, and the implications of that effect (Drydakis, 2015; 2016; Hoekstra, 2009). The study attempts to solve the problem of firms seeing more information than researchers by looking at an outcome that is determined before firms are influenced by any unobservable characteristics (Baert, 2018; Riach and Rich, 2002). Hence, the study's empirical methodology provides direct evidence of firms' potential preference for students with AI capital by 'catching' preferential treatments in the labour market (Riach and Rich, 2002). Correspondence tests are often ideal for identifying the causal effect of a change under real-world conditions, and therefore can be powerful for testing theories that make strong predictions (Phillips, 2019; Riach and Rich, 2002).

The outcomes of the present study indicate that AI capital positively affects employment prospects for graduates. When university classmates with similar qualifications apply for positions at the same firm, those applicants equipped with AI capital have higher chances of receiving interview invitations compared to their counterparts lacking such capital. Moreover, the study evaluates that possessing AI capital is linked to a positive wage sorting. Applicants with AI capital receive interview invitations for positions offering hourly wages that are higher than those without AI capital. Additionally, the study indicates that the size of the firm plays a crucial role in influencing the employment prospects of graduates. Large firms appear to favour job applicants with AI capital, leading to increased interview invitations and higher-paying job prospects. If AI influences businesses' operations, AI capital could be a critical element that learners should study to facilitate their employment prospects. Furthermore, policy actions targeting teaching curricula and training interventions to support individuals' AI capital, and firms' AI competencies, might be considered (Laupichler et al., 2022; Sollosy and McInerney, 2022; Drydakis, 2022b).

In the remainder of the paper, the next section defines AI capital and how it might relate to employment prospects. Section 3 describes the study's methodology in detail. Section 4 provides descriptive statistics, and Section 5 presents the results, followed by a discussion, and conclusions.

## 2. AI capital and employment prospects

### *2.1 AI tools in business*

Firms that adopt AI tools can enhance their competitive advantage, organizational performance, operational effectiveness, and productivity (Drydakis, 2022a; b; Laupichler et al., 2022; Sollosy and McInerney, 2022; Ulrich, Frank, and Kratt, 2021; Black and van Esch, 2020; Campbell et al., 2020; Chan et al., 2018).

Surveys have indicated that AI tools are used in the following business areas: (i) Marketing automatization systems and e-commerce; the aim is to improve customer targeting and interactions, based on their habits, social media activities and profiles, online activities, and past transactions. (ii) Digital communication with customers, to facilitate communication between humans and machines and provide personalized services to customers. (iii) Predictions, pricing, and cash flow, aiming to enable dynamic real-time pricing, demand response optimization, identify changes in competitor behaviour, and make rapid price adjustments. (iv) Cyber security, to offer protection from cyber-attacks and fake reviews; (v) Recruiting, to process information; and (vi) Legal services, in order to facilitate operations related to contract analytics, and mergers and acquisitions (Drydakis, 2022a; Drydakis, 2022b; Campbell et al., 2020; Laupichler et al., 2022; Sollosy and McInerney, 2022; Black and van Esch, 2020; Armour and Sako, 2020; Wu et al., 2020; Ikumoro and Jawad, 2019; Jablonska and Polkowski, 2017).

### *2.2 AI capital and employment prospects*

AI knowledge and the use of AI tools in business settings encompass a range of skills for individuals, including data analysis, decision-making, creativity and innovation, and communication (Acemoglu et al., 2022; Drydakis, 2022a; b; Laupichler et al., 2022; Sollosy and McInerney, 2022; Campbell et al., 2020). Individuals with AI skills can utilize AI tools to assist them in analysing large volumes of data more quickly and accurately than traditional analytical tools, thereby facilitating more informed and better data-driven decisions. Moreover, individuals with AI skills can use AI tools to access and evaluate a vast amount of information; this aids them in decision making, problem solving and predicting outcomes, such as pricing and cash flow, by assessing alternative solutions to complex business cases. Such features can support individuals in making more effective choices. In terms of creativity, those with AI skills can use AI tools to systematically generate and synthesize ideas, and propose innovative solutions based on data-informed scenarios. This capability is particularly valuable for individuals working in creative fields, such as marketing and business. Additionally, individuals with AI skills can use AI tools to facilitate communication by improving reports' structure, context, quality, and language translation, thereby helping employees communicate effectively with colleagues and clients. Jobs that require software and data analysis, cognitive (e.g., problem solving, creativity, information processing) and social skills are complementary to jobs that use AI tools (Alekseeva et al., 2021).

The present study defines 'AI capital' as 'a vector of knowledge, skills and capabilities related to AI technologies applied in business environments (amongst other areas), which could boost individuals' productivity, employment opportunities and earnings (amongst other payoffs)'. Knowledge refers to the information, facts, and understanding that an individual possesses. Skills are the practical features or expertise that individuals develop through practice and application of knowledge. Both knowledge and skills refer to the agency of individuals in augmenting their productivity (Sen, 1997). Capabilities encompass a broader set of attributes, combining both knowledge and skills to represent overall capacity and effectiveness. Capabilities focus on individuals' ability to perform the job tasks that they have been employed to do (Sen, 1997).

Because the term 'capital' means a stock or reserve of anything of social or economic significance (Hodgson, 2014), the introduction of a new capital, i.e. AI capital, aims to capture a vector of AI-related knowledge, skills and capabilities that can be linked to socioeconomic realities and outputs. AI capital is related to Bourdieu's (1983) discourse suggesting that 'capital' should be perceived as a set of resources and powers that can play critical roles in producing and reproducing profits in individuals' life opportunities (Ignatow and Robinson, 2017). AI capital evaluates the acquisition of AI-related knowledge and skills through investments in education and training; these acquired capabilities can subsequently translate into increased productivity. Within a business context, AI capital and its accumulation should facilitate the utilization of AI tools aimed at enhancing problem-solving and decision-making abilities, as well as aiding in the identification of business opportunities and challenges[2]. This facilitative role of AI capital should be recognized as a valuable and rewarding asset for firms, as long as it can contribute to improving firms' performance indicators.

Individuals possessing AI capital should demonstrate their knowledge (Becker, 1965), and/or signal their expertise in the field (Spence, 1973). Human capital theory asserts that an individual's knowledge forms their human capital, which can enhance productivity, employability, and earnings potential (Becker, 1965). Consequently, individuals might invest in education to develop their AI capital, anticipating improved employment prospects. As a result, individuals' accumulation of AI capital is expected to align with the utilization of AI tools in business operations. Moreover, signalling theory suggests that human capital can serve as a signalling mechanism, where individuals build their human capital not only for the skills it imparts, but also to signal their capabilities to potential employers (Spence, 1973). In light of this, firms may have a strong incentive to identify, screen, and employ individuals with AI capital, as it can lead to enhanced operational efficiency and productivity. Both the human capital theory and signalling models of education posit a positive impact of pertinent experience and specialization on individuals' likelihood of securing employment, and on their future earnings (Weiss, Klein, and Grauenhorst, 2014). In line with the human capital theory, any experience and specialization associated with AI can be seen as an additional accumulation of knowledge, deserving recognition in the labour market (Weiss, Klein, and Grauenhorst, 2014). Similarly, drawing from signalling

[2] In business environments, AI skills encompass knowledge in programming languages for developing AI tools, knowledge in machine learning, deep learning, and reinforcement learning for tasks such as data analysis, decision-making, predictive analytics, and forecasting; as well as knowledge of natural language processing for tasks including digital text analysis, chatbot development, and language translation (Drydakis, 2022a).

models of education, AI-related experience and specialization can function as an additional filter for assessing job applicants' data-driven skills and productivity (Weiss, Klein, and Grauenhorst, 2014).

Considering the arguments presented, the first hypothesis of the study proposes that:

*Hypothesis 1. In business environments, job applicants with AI capital have a greater probability of receiving an invitation to an interview compared to job applicants who lack AI capital.*

Large firms, i.e. with more than 250 employees, are investing in AI to maintain a competitive advantage (Igna and Venturini, 2023; OECD, 2021). Research indicates that small-to-medium firms face challenges in terms of infrastructure, resources, expertise and financial capability when adopting and implementing AI (Drydakis, 2022a; b; OECD, 2021; Cubric, 2020). Drawing on the Schumpeterian structural technological transformation theory (Schumpeter, 1939), large firms, owing to their higher market value, cash holdings and high innovation investments, may actively seek to integrate AI technologies into their operations and engage individuals with the necessary skills for emerging AI job tasks more than small-to-medium firms (Acemoglu et al., 2022; Sollosy and McInerney, 2022; Alekseeva et al., 2021; Hansen and Bøgh, 2021; OECD, 2021; Ulas, 2019). If AI skills, encompassing data analysis, decision making, creativity, innovation, and communication, are correlated with the ability to adapt to and excel in a rapidly evolving business landscape, those equipped with AI capital may be better positioned to seize new job opportunities (Cubric, 2020; Ulas, 2019). This advantage is particularly pronounced in large firms that are deeply involved in harnessing AI technologies and highly value those who can effectively utilize them (Acemoglu et al., 2022; OECD, 2021). Consequently, individuals with AI capital can offer a competitive edge to large firms by facilitating the development of their AI-based infrastructure, optimizing operations, and supporting strategic investments in innovation (Alekseeva et al., 2021).

Similarly, according to the skills mismatch theory (Freeman, 1976), if AI capital is becoming increasingly integral to large businesses, individuals with AI capital could be perceived as better prepared to meet the demands of the job market, and firms will enjoy enhanced overall efficiency and productivity. In large firms, individuals with AI capital may hold a competitive advantage in a job market that values multidisciplinary expertise, including specialization in business and AI tools (Acemoglu et al., 2022; Alekseeva et al., 2021; OECD, 2021; Cubric, 2020; Ulas, 2019). This might be particularly true in large firms that use AI tools, and/or employers who believe that individuals' AI capital can contribute to improving firms' performance (Hansen and Bøgh, 2021; OECD, 2021; Cubric, 2020).

Considering the arguments presented, the second hypothesis of the study posits that:

*Hypothesis 2. In business environments, job applicants with AI capital have a greater probability of receiving an invitation to an interview in large firms than in small-to-medium firms.*

Finally, the literature consistently demonstrates that large firms tend to provide higher wages to employees, compared to small-to-medium firms (Alekseeva et al., 2021; Barth, Davis, and Freeman, 2018; Waddoups, 2007; Troske, 1999). Large firms typically have more financial resources due to their scale of operations; they are also involved in more complex and extensive projects that incorporate various new technologies, and require a higher level of expertise from their workforce. Consequently, large firms are more inclined to offer higher wages to individuals capable of handling these tasks and complexities, as well as to attract and retain experts. There is evidence that job postings in large-scale firms demanding AI skills often come with wage premiums (Alekseeva et al., 2021), given that AI skills are expected to drive enhanced productivity (Alekseeva et al., 2021). Therefore, if large firms that provide higher wages seek to employ individuals with AI skills, it may be the case that job applicants with AI capital will experience higher wages in these large firms.

Considering the arguments presented, the third hypothesis of the study suggests:

*Hypothesis 3. In business environments, job applicants with AI capital experience higher wages in large firms compared to the wages offered in small-to-medium firms.*

### *2.3 Studying AI in business*

With the growing presence of AI tools in workplaces, universities have started to develop teaching materials for delivering AI knowledge to non-technical audiences (Xu and Babaian, 2021). These teaching initiatives are intended to build students' knowledge, skills and capabilities for collecting appropriate information for a certain case, analysing the data by applying logical reasoning, and applying problem-solving methodologies to real-world problems; hence, AI is becoming a tool deployed in this process (Sollosy and McInerney, 2022).

AI in business education should be about understanding and interpretation, strategizing, and ultimately, taking the actions necessary to further firms' interests and aims by using AI tools (Sollosy and McInerney, 2022). Studies examining AI in business curricula have found that the demand for AI competence motivates students from a variety of business majors (Xu and Babaian, 2021). Moreover, students with no computing background can successfully acquire AI competence and skills (Xu and Babaian, 2021).

Regarding the setting for the present study, in 2022, the 'AI in Business Environments' module was offered at a university in England, for third-year students studying economics. Prerequisites were taking modules in mathematics, statistics and econometrics. Considering the prerequisites, the module falls within the category of a moderately advanced level.

The scope of the module was to shape students' AI capital. The module aimed to introduce students to the fundamental principles underlying AI, in a process designed to realize the benefits and challenges of applying AI in a business environment, and to understand how AI can facilitate business processes (Laupichler et al., 2022; Ng et al., 2021). The module taught students what AI actually does, how it works, and what are the associated challenges, to enable them to make well-informed decision regarding the utilization of AI in business.

Students were presented with real-world examples of AI tools in business and the economy. Moreover, they were taught to build their critical capacity by identifying new business opportunities for applying AI. Students were shown the differences in goals, methods and settings between the machine learning approaches and the traditional econometrics and statistics methodologies. They were taught the use of algorithms to extract information and knowledge from data, aiming to develop their understanding of data as an asset for businesses and the economy.

The module was structured around 12 lectures and eight computer-based seminars, covering the following topics: (i) The fundamentals of AI, (ii) AI business opportunities, (iii) Ways to use AI tools in business, (iv) AI for strategy and decision making in business, (v) Ways to use AI tools in the economy, (vi) AI and machine learning, (vii) Opportunities and challenges afforded by machine learning to supplement econometric approaches, (viii) Machine learning in economics and business, (ix) Challenges and biases in AI tools, and (x) Ethical and legal considerations related to AI.

In the present study, to assess the hiring prospects of students who participated in the AI in business module, a correspondence test was conducted, involving both students who had studied the module and those who had not. The experimental design is presented in the next section.

## 3. Experiment structure

### *3.1 Correspondence tests*

A correspondence test enables researchers to investigate whether preferential treatment exists in the labour market (Riach and Rich, 2002). The methodology consists of researchers sending genuine or fictitious applications to real job vacancies. Most observed characteristics of a CV are controlled, e.g., age, ethnicity, race, gender, marital status, working experience, skills, hobbies, personality characteristics, other than a characteristic of interest, e.g., AI capital. Measuring preferential treatments is reduced to a simple comparison of call-back rates, i.e. invitations for a job interview, from firms (Riach and Rich, 2002).

Measuring preferential treatments can be problematic, because numerous unobservable or difficult-to-measure characteristics may correlate with a characteristic of interest (Phillips, 2019). It is not always valid to quantify a direct link between graduates' credentials and employment prospects, given that unobserved characteristics, such as students' motivation, commitment, ability, skills, and personality characteristics, may also be rewarded in the labour market (Hoekstra, 2009). In addition, students' socioeconomic background, such as family characteristics, parental support and networks, could affect their labour market outcomes, and thus some students may have greater employability and earnings capacity (Hoekstra, 2009; Drydakis, 2015; 2016).

In order to minimize the omitted-variable bias problem when evaluating the effect of AI capital on students' employment prospects, research should utilize two identical students with the same pre-university characteristics, who have studied the same subject in the same university; but only one student has attended an AI-related module. It should compare their hiring prospects when they search for a job. Therefore, through a correspondence test, the present study evaluates whether two comparable third-year university students who have obtained a degree in economics from the same university, but only one has enrolled in the 'AI in Business Environments' module, face different labour market prospects when applying to the same firms.

### *3.2 Design of the study*

After the end of the AI in business module, a call invited third-year economics students to participate in a correspondence test. The research team provided details of the intent and purpose of the designed correspondence test; they kindly requested students who were interested in searching for work to voluntarily take part in applied research beginning in August 2022, with the aim of evaluating how AI capital could affect job applicants' labour market prospects.

The call invited both students who had enrolled in the 'AI in Business Environments' module, and those who had not taken the module. The announcement indicated that, for a period of five months, the research team would provide each participant with random job openings relevant to their studies and record the correspondence from firms; in particular, they would note the number of invitations for job interviews. The call also stated that the acceptance of interviews would be at students' discretion.

The call invited potential participants to send their applications, i.e. cover letters and CVs, to the research team for review. The students' CVs had to include their demographic characteristics, pre-university qualifications, module studied and grade of degree, workplace experience, skills, personality characteristics, and hobbies.

The call indicated that each participant would receive a new university email account for research purposes, to which the research team would have access by default, in order to send the job applications and record correspondences from firms. The call explained the incentives that would be offered to encourage students to take part in the study, such as HR experts' help in building CVs, cover letters and job applications, and the provision of hundreds of subject-relevant job applications in England during a five-month period. Furthermore, there would be limited time involvement from participants, since the job applications preparation and sending was the research team's task. Moreover, the call mentioned that the participants would receive a certification regarding their experience in research design, data gathering, and database creation.

### *3.3 Matching profiles*

Upon receiving expressions of interest, the research team considered a number of criteria during the CV screening process to minimize the CVs' heterogeneity related to age, ethnicity, race, gender, and degree grades, among others. When these criteria were satisfied, the research team matched a male student who had undertaken the 'AI in Business Environments' module with a male student who had not studied the module. In addition, a female student who had studied the module was matched with a female student who had not done so. Hence, four students took part in the experiment.

Students who had not studied the ‘AI in Business Environments’ module had instead taken the ‘Business Environments’ module, and vice versa. Acceptance into ‘AI in Business Environments’ and ‘Business Environments’ was based on a first-come, first-served basis for students who had achieved a 2:1 (upper second-class) grade in mathematics, statistics and econometrics. Both module deliveries focused on business themes derived from the same core textbook, which explores business environments.

In the ‘AI in Business Environment’ module, AI themes were covered using a textbook focused on AI in business. In that module, during the computer-based seminars, R was utilized as the programming language. R packages were employed for statistical analysis and machine learning model development. Real-world business cases were examined, showcasing successful implementations of AI tools for data analysis, prediction, and recommendation systems in business environments.

In the ‘Business Environment’ module, business analytics themes were covered through a textbook on data analysis in business. In that module, during the computer-based seminars, R was used for data analysis. Real case studies were utilized to illustrate how to perform data analysis, prediction, and forecasting in business environments.

Hence, both groups of students had studied business environments, with one group specializing in AI techniques, while the other specialized in traditional econometric methods. The delivery in both modules was considered successful, based on students’ academic performance and anonymous feedback received at the end of the semester. In both modules, the average module grade was 2:1, and the overall student satisfaction rate was classified as excellent.

In all cases, the students who formed the matched pairs were 21 years old, of White British ethnicity, and unmarried. The students’ names and surnames were typical White British names. All students had studied microeconomics, macroeconomics, mathematics, statistics and econometrics. All students mentioned their knowledge in SPSS, STATA and R. The students held an upper second-class degree (i.e. 2:1). These demographic characteristics are common among UK university students (Drydakis, 2016; 2015; Brennan and Winnie, 2008). In the cover letters and CVs, the students did not mention any paid work experience.

Each student had a mobile telephone number, a postal address, and a university email address. To minimize biases, a matching procedure took place; the students declared university student accommodation as their address. In the matched pairs, students had attended state schools; were non-fee-paying, and had the same pre-university characteristics (A-Levels). To minimize further heterogeneities, the matched-pair students indicated identical skills (i.e. ability to work in teams, communication skills), hobbies (i.e. travel, cinema), and personality characteristics (i.e. likeable, friendly). Their personality characteristics (likeable and friendly) were evaluated as neutral (i.e. as neither feminine nor masculine), based on Bem's (1974) masculinity–femininity inventory. No photographs were included in the job applications.

*3.4 Signalling AI capital*

Students who had studied the 'AI in Business Environments' module (i.e. the treatment group) signalled their AI capital in a paragraph in the cover letter of their application, in accordance with the study's definition of AI capital.

The signalling paragraph indicated that 'As part of my university studies, I enrolled in a 12-lecture/8-seminar module examining Artificial Intelligence (AI) in Business Environments. I studied, with success, the fundamentals of AI, as well as ways to use AI in business. I practised with AI, using it for strategy and decision-making. I had the opportunity to apply AI and machine learning through business cases and I studied challenges associated with AI in business. The module enabled me to build my knowledge on AI fundamentals, develop my AI skills, and boost my capabilities when having to assess and use AI technologies in business environments'. Similar information was stated in applicants' CVs, as well as in the electronic standardized forms in the skills and/or training sections. The students who had enrolled in the 'AI in Business Environments' module were asked to reflect on the signalling information. Students confirmed that the utilized information captured the AI knowledge, skills and capabilities they had gained and developed through their AI in business module.

Students who had studied the 'Business Environments' module (i.e. the control group) indicated that 'I gained business experience through the projects I delivered as part of my semester module in Business Environments. I acquired knowledge regarding the practical application of business theories and concepts in business planning and strategy, as well as how businesses operate and how stakeholders make decisions. I studied how to analyse real business cases and propose policy action. I gained an understanding of the factors that influence business environments and developed the analytical skills needed to apply business knowledge to the real world'. The students who had studied the 'Business Environments' module were asked to reflect on the utilized information, and confirmed that the information captured the business expertise they had gained through their taught modules.

A pilot study was conducted to assess the consistency of the signalling information and experimental setting. HR and business managers were tasked with evaluating job applications from the treatment group and the control group using a scale of one to ten. They assessed the job applications of final-year students based on four criteria: knowledge in economics, business skills, analytical skills (i.e. ability to use and interpret data), and overall application quality. The HR and business managers were identified through commercial lists of firms maintained by the university's faculty. In total, 26 HR managers, and 59 business managers participated in the pilot study.[3]

[3] Approximately 50.6% of the pilot study's participants worked in small-to-medium firms, while the remainder worked in large firms The pilot study's participants were employed in occupations related to accounting (7.0%); business administration (11.7%); economics (7.0%); entrepreneurship (14.1%); finance (14.1%); insurance (10.5%); investment (10.5%); marketing (9.4%); retail (4.7%), and sales (10.5%).

The evaluations by HR managers did not reveal any statistically significant differences between the treatment group and control group's job applications in terms of knowledge in economics (8.230 vs 8.269, $t = -0.440$, $p = 0.663$), business skills (7.769 vs 7.807, $t = -0.327$, $p = 0.746$), analytical skills (8.307 vs 8.230, $t = 0.625$, $p = 0.537$), and overall application quality (8.192 vs 8.153, $t = 0.569$, $p = 0.573$). Similarly, the evaluations by business managers showed no statistically significant differences between the treatment group and control in relation to knowledge in economics (8.050 vs 8.016, $t = 0.389$, $p = 0.698$), business skills (7.847 vs 7.830, $t = 0.330$, $p = 0.742$), analytical skills (7.779 vs 7.661, $t = 1.095$, $p = 0.278$), and overall application quality (8.067 vs 8.033, $t = 0.629$, $p = 0.531$).

Moreover, the pilot study requested participants to identify any differences between the treatment group and control group's job applications, and indicate potential preferential treatments that these differences could imply in the job market. Qualitative reflections revealed that the AI capital signal in the treatment group's job applications consistently appeared as the actual difference between the job applicants that could attract positive evaluations from employers interested in AI technologies. HR and business managers commented as follows: 'AI is increasingly integral to daily work; candidates should be familiar with AI for their respective positions', 'The integration of AI offers significant advantages and opportunities for both businesses and the workforces', 'AI skills are highly desirable in today's job market', 'Graduates can enhance their chances of securing a good job by acquiring AI skills', 'Unfortunately, there is currently a shortage of mid-level and senior-level staff with expertise in AI. Firms are particularly impressed when job applicants have undergone AI training', 'Due to the high competition in the labour market, graduates who prominently highlight unique traits, such as AI expertise, on their CVs are more likely to attract recruiters' attention', 'Firms recognize the value of AI and the numerous opportunities available to those with AI expertise', and 'Companies prioritize the recruitment and development of an AI-skilled workforce'.

The pilot study indicated that the study's experimental design enabled the treatment group to effectively signal their AI specialization, which could attract firms interested in AI technologies – all while ensuring that all job applications were of comparable quality, and emphasized similar knowledge in economics and business, as well as analytical skills. Furthermore, there was a unanimous agreement that no demographic characteristics or other factors led to preferential treatment.

### *3.5 Application sending and sample characteristics*

In order to address the study's research objective, the research team collected data between August and December 2022. The job-seekers applied for entry-level business jobs relevant to their studies in England by sending out their application forms. The study focused on job openings in the private sector for graduates. It is indicated that the public sector might be more weakly constrained by profitability requirements than the private sector (Laurent and Mihoubi, 2012). Hence, a focus on young people in the private sector is more appropriate in correspondence tests (Drydakis, 2016; 2015). The vacancies were identified through a random sample of advertisements that appeared on leading internet websites which advertised job openings. The large number of job search websites suggests that these sites are a typical resource for job-seekers in England.

The research team submitted job applications twice a week, reaching out to a total of 1,338 firms. In 680 firms, a matched pair of male applicants, one with AI capital and the other without AI capital, submitted applications, resulting in a total of 1,360 applications from male applicants. In 658 firms, a matched pair of female applicants, one with AI capital and the other without AI capital, submitted applications, resulting in a total of 1,316 applications from female applicants. Hence, a total of 2,676 job observations were submitted.

In the total sample, the distribution of occupations is as follows: accounting (7.8%); business administration (10.1%); economics (7.9%); entrepreneurship (6.9%); finance (10.2%); insurance (8.8%); investment (11.7%); marketing (12.9%); retail (11.7%); and sales (11.6%).

Having access to applicants/students' email accounts, the research team recorded invitations for interviews.

The firms received application submissions electronically. The applications consisted of filling a standardized electronic form, and/or uploading documents such as a cover letter and a CV. In the sample, 66.3% of the firms required a standardized electronic form. In order to control for the possibility that the style of an application (the ways in which textual elements were organized and formatted, e.g., wording, headings, fonts, font sizes) influenced a firm's response, two different types of matched pairs of applications were utilized. The applications were posted simultaneously within one day of the advertisement's appearance, and there was an alteration of the sending order for each matched pair of applications.

For research purposes, the research team screened the webpages of the firms that advertised the job openings, and recorded whether the firms were classified as either small-to-medium or large. In the sample, 58.4% of the job openings were from small-to-medium firms. Moreover, the research team collected data on wage sorting. This was achieved by recording the job's wage if a vacancy advertised the relevant information (Drydakis, 2009). In doing so, the research team was able to assess whether students with AI capital had access to those positions that offered higher wages.

The design of the present study made it possible to reduce common biases in experimental studies. Applicants used official university emails and university student accommodation as their residential addresses. These features are expected to increase the credibility of the applications and decrease the likelihood of detection by recruiters, which results in a decline in correspondence (Weichselbaumer, 2015). In addition, these credibility features would reduce recruiters' potential beliefs regarding differences in the unobserved productivity of applicants with and without AI capital – the so-called Heckman–Siegelman critique (Heckman and Siegelman, 1993). In this study, observables (i.e. place of residency, workplace experience, hobbies, personality characteristics, ethnicity, etc.) were not randomized. Thus, the Heckman–Siegelman critique is not testable.

## 4. Results

### *4.1 Access to occupations*

In the academic years 2020-2022, according to official UK University League Tables data on career outcomes after graduation, statistics indicate that for economics graduates at the university under examination, the percentage of graduates who secured graduate-level jobs was approximately 90%. The patterns suggest that economics graduates from that university are competitive in the labour market, both in terms of invitations to job interviews and actual offers from employers. In the current study, and across the entire sample, approximately 4 invitations for interviews were documented for every 10 job applications (41.1%). The rate reduced to around 3 invitations for interviews for every 10 job applications (29.9%) when these originated from applicants without AI capital.

Concerning the pair of male applicants, in 181 cases, both applicants were invited for an interview (26.6%). In 188 cases, only the applicant with AI capital was invited (27.6%), and in eight cases, only the applicant without AI capital was invited for an interview (1.1%). The difference represents 180 cases (26.4%). The outcome is statistically significant at the 1% level ($x^2 = 165.3$).

For the pair of female applicants, in 190 cases, both applicants were invited (28.8%). In 141 cases, only the applicant with AI capital was invited (21.4%), and in 22 cases, only the applicant without AI capital received an invitation (3.3%). The difference between the two applicants represents 119 cases (18%). The outcome is statistically significant at the 1% level ($x^2 = 86.8$).

### *4.2 Wage sorting*

Regarding the wage prospects for those who received invitations for interviews, male applicants with AI capital were sorted in jobs offering wages (i.e., logged hourly gross wages) that were, on average, higher than those for male applicants without AI capital: 2.92 (n=192) compared to 2.80 (n=94). The difference is approximately 12.3% ($t = 6.9$, $p<0.01$).

Similarly, female applicants with AI capital were sorted in jobs offering wages that were, on average, higher than those for their counterparts without AI capital: 2.88 (n=156) compared to 2.75 (n=94). The difference is approximately 13.3% ($t = 7.0$, $p < 0.01$).

## 5. Estimates

*5.1 Access to occupations*

Table 1, presents the marginal effects derived from probit estimates (Wooldridge, 2010). Each model controls for application style, sending order, electronic standardized forms, firm size, and occupation fixed effects.

Model I shows that the male applicant with AI capital has a 27.1 percentage point ($p < 0.01$) higher chance of receiving an invitation for interview than the male applicant without AI capital. Model II estimates an interaction effect between AI capital and firms' size. It is found that in large firms, the male applicant with AI capital has a 36.2 percentage point ($p < 0.01$) higher chance of receiving an invitation for interview than in small-to-medium firms.

Model III shows that the female applicant with AI capital has a 18.5 percentage point ($p < 0.01$) higher chance of receiving an invitation for interview than the female applicant without AI capital. In addition, Model IV illustrates that in large firms, the female applicant with AI capital has a 36.1 percentage point ($p < 0.01$) higher chance of receiving an invitation for interview than in small-to-medium firms.

Models V and VI pool data for the male and female applicants. Model V indicates that applicants with AI capital have a 22.7 percentage point ($p < 0.01$) higher chance of receiving an invitation for interview than applicants without AI capital. Model VI denotes that in large firms, applicants with AI capital have a 35.9 percentage point ($p < 0.01$) higher chance of receiving an invitation for interview than in small-medium firms. Based on the outcomes of the study, both Hypotheses 1 and 2 can be accepted.

[Table 1]

*5.2 Wage sorting*

Table 2 presents the wage prospects for those who received invitations for interviews. Ordinary Least Squares logged hourly gross wages are reported (Wooldridge, 2010). Each model controls for application style, sending order, electronic standardized forms, firm size, and occupation fixed effects.

In Model I, it is observed that the male applicant with AI capital was invited to interviews for vacancies that offered 10.2% ($p < 0.01$) higher hourly wages than for the male applicant without AI capital. Model II shows that in large firms, the male applicant with AI capital was invited to interviews for vacancies that offered 8.9% ($p < 0.01$) higher hourly wages, compared to small-to-medium firms.

In Model III, it is estimated that the female applicant with AI capital was invited to interviews for vacancies that offered 10.6% ($p < 0.01$) higher hourly wages than the female applicant without AI capital. Model IV presents that in large firms, the female applicant with AI capital was invited to interviews for vacancies that offered 13.1% ($p < 0.01$) higher hourly wages than in small-to-medium firms.

Models V and VI pool data for the male and female applicants. In Model V, it is found that applicants with AI capital were invited to interviews for vacancies that offered 10.5% ($p < 0.01$) higher hourly wages compared to applicants without AI capital. Model IV indicates that in large firms, applicants with AI capital were invited to interviews for vacancies that offered 10.8% ($p < 0.01$) higher hourly wages than small-to-medium firms. Based on the outcomes of the study, Hypothesis 3 can be accepted.

[Table 2]

## 6. Discussion

This study defined the term 'AI capital', aiming to develop a conceptual framework that captures the knowledge, skills and capabilities related to AI. Then, AI capital's employment prospects were assessed in the labour market. The outcomes of the study indicated that AI capital was valued in the labour market. Applicants with AI capital experienced higher access to job vacancies, and were sorted into better-paid jobs. The study's outcomes were found to hold for both male and female applicants.

The outcomes of the present study indicated that AI capital in business studies might be a valuable productivity and employment trait. Job applicants with AI capital might possess the knowledge, skills and capabilities related to data analysis, data-driven decision-making, creativity, innovation, and effective communication, among other factors. These skills can enhance business operations, making them more efficient and potentially contributing to increased productivity within a firm. These findings are in line with the theoretical predictions on educational investments and positive rewards in the labour market, i.e. human capital theory (Becker, 1965) and signalling models of education (Spence, 1973).

The present study found that job applicants with AI capital were treated favourably in large firms, experiencing both higher access to occupations and better wage prospects. This preference might be due to the fact that large firms tend to undergo more extensive AI-based structural technological transformations (Schumpeter, 1939) due to their greater capacity for innovation (Igna and Venturini, 2023; Alekseeva et al., 2021; OECD, 2021). If AI tools are integral to the operations of large firms (Acemoglu et al., 2022; Hansen and Bøgh, 2021; Ulas, 2019), job applicants with AI capital might be perceived as better prepared to meet the evolving business needs of their organizations. Moreover, if large firms view AI tools as a strategic investment (Alekseeva et al., 2021; Hansen and Bøgh, 2021; Cubric, 2020), they might be more likely to hire individuals with AI capital to lead and drive these initiatives. Furthermore, if large firms provide higher wages to a specialized workforce, then individuals with AI capital will be sorted into large and better-paying firms (Acemoglu et al., 2022; Alekseeva et al., 2021; Barth, Davis, and Freeman, 2018; Waddoups, 2007; Troske, 1999).

In the UK, AI is causing dramatic shifts in the workforce, and firms need to respond to these demands by upgrading their workforces via enhancing their AI-skill levels (McKinsey and Company, 2019). The UK National AI Strategy (HM Government, 2021) aims to ensure that the country can both develop and use AI for the benefit of citizens. The strategy focuses on ensuring that (i) the country invests in the long-term growth of AI; (ii) that AI benefits all sectors and regions of the economy; and (iii) that it is governed effectively by adequate rules which encourage innovation, investment, and protect the public and the country's fundamental values (HM Government, 2021).

The challenge for universities and business faculties lies in preparing students to be professionals who understand business needs, who can interpret the analysis performed on large data sets by AI, and can offer data-informed decision making (Sollosy and McInerney, 2022; Chiang, Goes, and Stohr, 2012). Policies might encourage university faculties to consider forming and enhancing students' AI capital in their own disciplines by adapting the curriculum and teaching.

*6.2 Limitations and future research*

As the study focused on a single region of the UK, additional regions should be examined to confirm the presented outcomes. It might be the case that in less technology-intensive regions, AI capital is less rewarded in the labour market. Moreover, the study examined the labour market prospects of economics graduates. There is a need to consider additional fields of studies, as it might be expected that in certain professions, i.e. STEM fields, AI capital is more rewarded. The 'AI in Business Environments' module makes it necessary for students to have knowledge in mathematics, statistics and econometrics. This requirement appears crucial for replicating the results in different professions, thereby underscoring the module's significance.

The study utilized a dichotomous classification to empirically assess AI capital's employment prospects. Future research should consider the job applicants' level of AI capital, as advanced AI skills might result in higher employment prospects. It is also important to evaluate which specific AI skills are most valued by firms and rewarded in the labour market.

The study did not examine whether, in certain occupations, applicants with AI capital were treated more favorably. Therefore, a new study should investigate the returns of AI capital in different occupations. Although the study controlled for occupational fixed effects, and firms' size, critical information on industrial characteristics is missing. Thus, future research should collect information on firms' turnover and gross assets, to bring further insights. Furthermore, job applicants might apply for jobs they have learned about through their networks, such as parental and friends' support; hence, the present study does not account for situations in which applicants do not use internet websites to identify job openings (Sostero and Fernández-Macías, 2021). Finally, correspondence tests observe preferential treatments during the job interview stage, but they do not track job applicants' success rates in securing job offers.

## 7. Conclusion

The study proposed the term 'AI capital' which encompasses a vector of knowledge, skills, and capabilities related to AI technologies. This capital has the potential to enhance individuals' productivity, employment opportunities, and earnings. The study then presented the outcomes of a genuine correspondence test conducted in England. It revealed that university graduates with AI capital, acquired through an AI business module, received more job interview invitations than graduates without AI capital. Furthermore, applicants with AI capital were invited to interviews for positions that offered higher wages than those without AI capital. Notably, it was estimated that large firms exhibited a preference for job applicants with AI capital, resulting in increased interview invitations and opportunities for higher-paying positions. The study concluded that AI capital could impact employment prospects, particularly in large firms.

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| **Table 1. Access to vacancies estimates** | | | | | | |
|---|---|---|---|---|---|---|
| | **Male applicants** | | **Female applicants** | | **Male and female applicants** | |
| | **Model I** | **Model II** | **Model III** | **Model IV** | **Model V** | **Model VI** |
| Applicants with AI capital^ | 0.271<br>(0.025)*** | 0.108<br>(0.037)*** | 0.185<br>(0.026)*** | 0.061<br>(0.034)* | 0.227<br>(0.018)*** | 0.059<br>(0.030)* |
| Large firms^^ | 0.090<br>(0.028)*** | -0.100<br>(0.040)** | 0.018<br>(0.029) | -0.168<br>(0.040)*** | 0.058<br>(0.020)*** | -0.128<br>(0.028)*** |
| Applicants with AI capital^<br>× Large firms^^ | - | 0.362<br>(0.051)*** | - | 0.361<br>(0.053)*** | - | 0.359<br>(0.037)*** |
| Men | - | - | - | - | -0.009<br>(0.019) | -0.035<br>(0.028) |
| Applicants with AI capital^<br>× Men | - | - | - | - | | 0.049<br>(0.040) |
| LR $x^2$ | 153.74 | 196.68 | 97.51 | 136.20 | 218.52 | 304.85 |
| Prob>$x^2$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Pseudo $R^2$ | 0.083 | 0.106 | 0.054 | 0.076 | 0.060 | 0.084 |
| Observations | 1,360 | 1,360 | 1,316 | 1,316 | 2,676 | 2,676 |

*Notes: Each model presents the marginal effects derived from probit estimates. Each model controls for application style, sending order, electronic standardized forms, and occupation fixed effects. (^) The reference category is applicants without AI capital. (^^) The reference category is small-to-medium firms. (***) Statistically significant at the 1% level. (**) Statistically significant at the 5% level. (*) Statistically significant at the 10% level.*

**Table 2. Wage sorting estimates**

| | Male applicants | | Female applicants | | Male and female applicants | |
|---|---|---|---|---|---|---|
| | **Model I** | **Model II** | **Model III** | **Model IV** | **Model V** | **Model VI** |
| Applicants with AI capital^ | 0.102 (0.017)*** | 0.061 (0.023)*** | 0.106 (0.018)*** | 0.060 (0.022)*** | 0.105 (0.012)*** | 0.070 (0.019)*** |
| Large firms^^ | 0.077 (0.017)*** | 0.015 (0.029) | 0.087 (0.018)*** | -0.001 (0.031) | 0.081 (0.012)*** | 0.007 (0.021) |
| Applicants with AI capital^ × Large firms^^ | - | 0.089 (0.034)*** | - | 0.131 (0.038)*** | - | 0.108 (0.025)*** |
| Men | - | - | - | - | 0.032 (0.012)*** | 0.045 (0.019)** |
| Applicants with AI capital^ × Men | - | - | - | - | - | -0.018 (0.024) |
| F | 6.27 | 6.43 | 6.14 | 6.77 | 12.76 | 12.69 |
| Prob>F | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $R^2$ | 0.244 | 0.263 | 0.267 | 0.302 | 0.269 | 0.294 |
| Observations | 286 | 286 | 250 | 250 | 536 | 536 |

*Notes: Each model reports OLS logged hourly wages. Each model controls for application style, sending order, electronic standardized forms, and occupation fixed effects. (^) The reference category is applicants without AI capital. (^^) The reference category is small-to-medium firms. ***Statistically significant at the 1% level. **Statistically significant at the 5% level.*