

Exploring Barriers to AI Doctoral Studies

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Introduction

The present review aims to identify potential barriers to PhD/Doctoral studies on AI (Artificial Intelligence) in Bristol and the United Kingdom. To achieve this, a team of researchers from the University of Bristol has conducted a literature review of relevant studies across disciplines. Following brainstorming (*Figure 1*), three main areas of focus were identified, that is, socio-economic, AI-literacy, and AI-policy related barriers.

To understand why the doctoral pipeline remains exclusive despite high demand, this report examines barriers across three interconnected dimensions. First, we examine *Socio-Economic Barriers* (Section 1), exploring how systemic inequalities in gender, race, and finance filter out talent before they apply. Second, we analyse *Individual Barriers* (Section 2), specifically the role of ‘AI Literacy’ and self-efficacy as psychological gatekeepers. Finally, we investigate *Structural Barriers* (Section 3), using a primary analysis of 2,643 live PhD listings to reveal how institutional policy and market mechanisms actively reinforce these exclusions.



Figure 1. Brainstorming process for identifying barriers to AI PhD/Doctoral studies

Before delving into the literature review, it is important to briefly illustrate how ‘AI’ is understood as part of this work. Empirical definitions of AI remain scarce and inconsistent,

which can affect both research findings and cross-study comparisons (Kelly et al., 2023). Nevertheless, the most widely used definition conceptualises AI as computer systems designed to perform tasks that typically require human intelligence, such as learning, problem-solving, and reasoning (MIOIR, 2025). Consistent with the above definition, some scholars suggest that AI can also be used to understanding natural language, recognising patterns, and making decisions (Kalim et al., 2025; Patole et al., 2024). For the purpose of the present review, it is also relevant to understand what it is meant by AI acceptance, or else, the intention or willingness to use, buy, or try AI systems (Kelly et al., 2023). AI is generally used to process existing data (normally referred to as processing AI) or to create new content (generative AI) (Bahn and Strobel, 2023, Ulnicane, 2025). While alternative socio-technical and critical definitions of AI may exist, the above functional definitions seem to underpin the literature reviewed here and reflect dominant usage of AI across education and policy research.

To ground this review in the UK's current doctoral landscape, we complemented our literature analysis with a primary study of active recruitment data. Using a custom NLP pipeline on 2,643 listings from FindAPhD.com (December 2025), we mapped patterns in funding, eligibility, and entry requirements. This empirical approach tests the theoretical barriers identified in our brainstorming (Fig. 1), revealing exactly how abstract policy issues manifest as concrete obstacles in the recruitment of future AI researchers.

Literature Review

1. Socio-economic Barriers to Doctoral Studies In AI

This section examines barriers to PhD studies in Artificial Intelligence (AI), with a particular focus on socio-economic factors that may hinder access to and progression within doctoral education in AI. It also explores the bidirectional relationship between socio-economic inequalities in AI education and broader inequalities within the AI ecosystem, including those related to governance, labour markets, and research production. Specifically, inequalities in access to AI doctoral studies shape who produces AI research and who

participates in AI-related decision-making, while existing power imbalances in AI research and industry, in turn, influence educational opportunities.

Drawing on a review of relevant literature, the chapter identifies key barriers to engagement with AI in doctoral contexts. It first discusses broad barriers to AI adoption among doctoral students before turning to specific socio-economic dimensions shaping engagement with AI, including gender, geography, and race and ethnicity. The chapter concludes with a summary of findings and a set of policy- and research-oriented recommendations.

1.1. Reflecting On the Literature

The literature search was conducted with support from the University of Bristol subject librarian, who advised on search strategies, platforms, and terminology. Searches were carried out using Web of Science, Scopus, ERIC, Google Scholar, and Research Rabbit. Key search terms included socio-economic, poverty, financial inequality, doctoral, PhD, postgraduate, gender inequality, artificial intelligence, AI, ChatGPT, and Copilot.

The review revealed a substantial gap in studies directly examining socio-economic barriers to AI studies in higher education, particularly at the doctoral level, a limitation also noted by other scholars (e.g., [Kalim et al., 2025](#)). While a growing body of research addresses undergraduate and master's-level participation in AI, doctoral education remains comparatively underexplored. To address this gap, the review included studies on closely related topics (as revealed by the existing literature), such as STEM (Science, Technology, Engineering, Mathematics) education, AI-related authorship, and workforce participation. In addition to peer-reviewed academic articles, relevant reports and scholarly blogs were also included.

Most identified studies focused on skills gaps in relation to labour-market demands and proposed strategies to mitigate their impact. The literature was heavily dominated by studies conducted in the United States (e.g. Ferguson et al., 2023), with fewer contributions from the UK and other global contexts (e.g. [Ulnicane, 2025](#)). This geographic imbalance reflects broader concentrations of research funding, data availability, and publication

practices, and limits the generalisability of findings across contexts.

Socio-economic barriers were most frequently discussed in relation to gender, typically operationalised as men and women, followed by race and or ethnicity. Other dimensions were often, if not always, overlooked, including age (e.g., mature students), disability, neurodiversity, migration status, or LGBTQ+ identities. This points to a significant gap in the current literature on equity, diversity, and inclusion (EDI) in AI-related education. Consistent with these observations, a cross-cutting theme across the reviewed literature is the need for accurate data and robust methodologies to better understand EDI dynamics in AI and STEM higher education.

1.2. Socio-economic Barriers to AI Adoption

One of the few studies explicitly examining AI adoption (as a tool to support their research) among doctoral students is that of Oliveira et al. (2024). The above study was conducted at the University of Texas at Tyler. Although context-specific, the study offers valuable insights given the broader lack of research in this area. While doctoral students generally recognised the efficiency and usefulness of AI tools, ethical concerns, particularly those related to academic integrity, ethical standards, and the unknown long-term impacts of AI, emerged as major barriers to adoption.

Technological dependence was another key concern. Participants expressed ambivalence towards AI's transformative potential. Although they acknowledged its utility, some reported negative emotional responses associated with a perceived loss of agency and autonomy in academic work. Scepticism also stemmed from the perception that AI-generated outputs lack genuine human thinking and articulation, raising concerns about originality and scholarly voice. While the authors do not further delve into sociodemographic characteristics, they highlight how different demographic groups might be more or less impacted by the academic culture around AI studies with unrepresented groups potentially being more sceptical about it due to culture (e.g., Kalim et al., 2025; Kelly, et al., 2023) and literacy.

The following sections examine how these general barriers intersect with specific socio-economic dimensions, beginning with gender.

1.2.1. Gender And Its Intersections with Other Socio-cultural Factors

Gender inequality represents one of the most significant barriers to participation in AI doctoral studies. While gender disparities in education have long been documented ([van de Werfhorst, 2017](#)), the growing integration of AI into academia may be reinforcing existing inequalities rather than mitigating them ([Stanford University, 2023](#)).

Evidence from multiple studies, reports, and institutional analyses (e.g. [Frachtenberg & Kaner, 2022](#); [Kalim et al., 2025](#); [MIOIR, 2025](#); [Stathouloupoulos et al., 2019](#)) consistently shows that white men are significantly overrepresented in AI-related doctoral studies, conference presentations, and academic authorship, all of which are closely tied to early academic careers in AI. Although overall participation in AI PhD research increased between 2000 and 2020, STEM doctoral theses remain predominantly authored by men, particularly in AI-related fields ([MIOIR, 2025](#)).

One potential explanation lies in the gender composition of supervisory staff. Approximately 73.4% of AI PhD supervisors are male (UK data; [MIOIR, 2025](#)), a figure that reflects broader patterns within computer science and engineering. This imbalance may discourage women from pursuing AI doctorates and limit their access to professional networks, mentorship, and career opportunities ([MIOIR, 2025](#)). While the exact relationship between the gender composition of supervisory staff and that of doctoral students is not clear, it could be argue that male prevalence within the field may build the perception that AI is predominantly a male discipline.

AI is a specialised field but is embedded within broader STEM disciplines such as computer science, engineering, and mathematics ([MIOIR, 2025](#)). Patterns of gender segregation in STEM therefore provide valuable insight into women's underrepresentation in AI doctoral studies. Structural and cultural barriers identified in STEM appear to carry over into AI education and research. Van de Werfhorst (2017) provides empirical evidence of persistent

gender segregation across post-secondary fields of study, particularly among students from lower socio-economic backgrounds. This highlights the intersection of gender and socio-economic status, suggesting that women from disadvantaged backgrounds are especially unlikely to pursue AI PhDs.

Additional factors further contribute to women's underrepresentation in AI. A systematic review by Kalim et al. (2025), focusing on Asian higher education contexts, found that women often report lower familiarity with AI tools, largely due to limited access to training, institutional support, and AI literacy programmes. Reduced familiarity, in turn, lowers AI adoption rates. Traditional gender roles and stereotypes also discourage women from entering AI-related studies and careers, as women are often expected to pursue occupations centred on care, communication, and human interaction (Kalim et al., 2025).

Gender bias embedded within AI algorithms themselves may further reinforce exclusion, particularly when biased systems shape educational assessment, recruitment, or research visibility. Moreover, women are frequently underrepresented in AI policy frameworks, limiting their influence on decision-making and the development of inclusive AI practices (Kalim et al., 2025). Women also tend to report greater concerns about privacy, data security, and the ethical implications of AI use (Kalim et al., 2025). These concerns, often linked to limited familiarity with AI tools, may further reduce engagement with AI technologies.

1.2.2. Authorship

Consistent with the patterns described above, studies examining AI-related authorship reveal substantial gender disparities (Ding et al., 2025; Frachtenberg & Kaner, 2022; Stathoulopoulos et al., 2019). Frachtenberg and Kaner (2022), using the female author ratio as a proxy measure, found that women accounted for only 10.26% of authors in leading AI-related systems conferences worldwide.

Similarly, Ding et al. (2025), drawing on the AI Scholar dataset, showed that women represented approximately 14 to 17% of AI researchers between 1980 and 2022. Although

this proportion has increased slightly over time, the gender gap remains persistent. Male-authored publications also tend to receive more citations, partly due to men's greater participation in larger, male-dominated collaboration networks and citation practices.

It is important to note that these studies typically rely on binary gender classification based on names, which excludes non-binary researchers and may underestimate inequality. Furthermore, the "leaky pipeline" phenomenon, whereby women disproportionately exit academic careers at early stages, likely contributes to their continued underrepresentation in AI publications (Ding et al., 2025).

1.2.3. Location and Its Intersection with Gender

Geography plays a major role in shaping access to AI education, research, and careers. A study analysing AI professionals' LinkedIn profiles found that half of the sample was concentrated in just four countries, the USA, France, Germany, and the UK, while more than 50 countries were each represented by less than 1% (Young et al., 2023). This finding highlights a strong geographic concentration within the AI labour market.

Geographic disparities become particularly pronounced when intersecting with gender. For example, approximately 30% of AI papers in the Netherlands included at least one female co-author, compared with only 10 to 16% in Japan and Singapore. Countries such as Malaysia, Denmark, Norway, and Israel demonstrate relatively stronger female representation in AI research (Stathoulopoulos et al., 2019).

Within AI, certain subfields, such as machine learning and data science, show especially low probabilities of female authorship. Notably, research co-authored by women tends to focus more on applied and socially oriented topics, including fairness, health, mobility, and gender. This pattern reflects, and may also reinforce, the traditional gendered expectations discussed earlier.

1.3. Race And Ethnicity

Underrepresentation typically refers to groups that have experienced historical

discrimination (Kuhlman et al., 2020). Across contexts, individuals from Black, Asian, and Latinx backgrounds face reduced access to AI and STEM education and employment (Roberts et al., 2021; Ferguson et al., 2023).

In the UK, a report by the UK Council for Graduate Education (UKCGE, 2024) found that 74% of postgraduate research students were white, compared with 5% Black and 9% Asian students. Economic barriers were identified as a major factor affecting completion and progression among ethnic minority students (UCL, 2025).

Longitudinal research in STEM further shows that Black students are less likely to graduate with top degree classifications (Low & Kalender, 2024). While representation of ethnic minorities in computer science has improved over time, white men continue to dominate undergraduate, master's, and doctoral levels (Stanford University, 2023). Despite progress, significant inequalities persist, particularly at the intersections of race, gender, poverty, and disability.

1.3.1. The Socio-economic Inequalities Loop In AI

Governance, Politics, and Geography

Barriers to AI doctoral education reflect broader inequalities within the AI ecosystem (Kuhlman et al., 2020). A systematic review by Shams et al. (2025) highlights the underrepresentation of the Global South in AI research, governance, and labour markets. AI governance is shaped by political and economic power, with decision-making dominated by actors in the Global North (Vargas-Solar, 2025; Young et al., 2023). A limited number of countries, alongside a small group of large technology companies, appear to control much of the generative AI landscape (see study introduction for definition).

Democratic and participatory co-shaping of technology is therefore essential to address the unequal distribution of power in generative AI. Governments play a crucial role in ensuring equal access to AI through education policy, funding, regulation, and public infrastructure, and in addressing power imbalances both within societies and across socio-ecological levels (Ulnicane, 2025).

The previously mentioned factors contribute to algorithmic bias reinforcing further inequalities, hence barriers. Although often framed as a technical problem requiring technical solutions, scholars argue that educational diversity and inclusion offer a more sustainable and just approach to addressing global systemic AI inequalities (Shams et al., 2025).

Job Market Inequalities and Education

Decisions to pursue AI careers are shaped by confidence in technical and interpersonal skills, perceptions of social impact, and professional identity (Ferguson et al., 2023). Women often report lower confidence in their abilities despite holding higher formal qualifications, a pattern widely observed across STEM and Information and Communication Technology (ICT) fields (Young et al., 2023). They also face stereotyping, lower pay, limited career advancement, and greater exposure to hostile work environments and microaggressions, all of which contribute to higher attrition rates (Ferguson et al., 2023; Young et al., 2023).

Evidence from STEM and ICT fields suggests that negative, gendered workplace cultures, excessive competition, and a lack of visible role models discourage women and minority groups from pursuing educational pathways that lead to AI careers (Fakoor Harehdasht & Saki, 2025; Williams et al., 2025).



Figure 2: A thematic mapping of socio-economics barriers interrelations.

1.4. Conclusion and Recommendations

To reduce socio-economic barriers to AI doctoral studies, universities in the UK and the USA have proposed similar strategies, including diversifying admissions panels, offering bridging programmes to address skills gaps, and implementing structured mentorship schemes (Roberts et al., 2021). In countries such as Finland and Sweden, higher female participation in AI has been linked to targeted funding, gender quotas, and participation-focused initiatives (Vargas-Solar, 2025).

There is an urgent need to expand EDI-focused research in AI doctoral education to develop evidence-based, context-sensitive strategies. Educators integrating AI tools into doctoral training must not only promote technical proficiency but also actively challenge exclusionary academic cultures and stereotypes. Clear ethical guidelines, training that complements rather than replaces human skills, and strong support systems can help alleviate concerns related to loss of agency and academic integrity.

Future research should also examine the psychological and behavioural dimensions of AI adoption, including its impact on academic identity and professional trajectories. More empirical evidence is needed to assess AI's effects on learning outcomes, research quality, and critical thinking, as well as the risks associated with over-reliance on AI tools.

Given the links between secondary education pathways and postgraduate AI participation, scholars advocate for gender-sensitive career guidance, targeted mentoring for students from lower socio-economic backgrounds, and policies encouraging gender balance across technical and care-related fields. Systematic monitoring of gender and socio-economic segregation is essential to evaluate policy effectiveness over time.

Finally, although inequalities in access to AI doctoral studies can be highly context-specific, the use of global literature does not necessarily constitute a limitation in this chapter. UK higher education is inherently international and multicultural, with doctoral cohorts often comprising students and staff from diverse geographic, cultural, and socio-economic backgrounds (Universities UK International, 2024).

Drawing on studies conducted outside the UK, including research from Asia (e.g. Kalim et al., 2025), therefore enhances rather than limits the relevance of this review when examining barriers to AI doctoral studies. At the same time, while socio-economic barriers may share common structural roots across countries, context-specific evidence remains essential, particularly when informing policy recommendations within the UK higher education system (Vargas-Solar, 2025).

2. AI Literacy

AI literacy is defined by Long and Magerko (2020) as:

“a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace”.

This is currently the most widely accepted definition in academic literature (Zhang et al.,

2025). It emerged from the concepts of digital literacy¹, information literacy and media literacy², emphasising ethical knowledge, critical thinking and interpretive skills (Chen et al., 2024; Lu and Lin, 2025). AI literacy has a proven positive effect on career intention and interest (Zhang et al., 2025a), indicating that it could be used to examine prospective candidates' interest and aptness for doctoral studies in AI.

Although the link between AI literacy and career intention is not always made explicit, the importance of AI literacy for education and society as a whole is mentioned in grey literature globally (Elhussein et al., 2024; Mendigutxia, 2024; *AI-REAL Toolkit*, 2025; Murphy et al., 2025; Kyle, 2025). Academic literature also considers the links between other recent constructs like AI self-efficacy³ (Chen et al., 2024; Duong, 2025; Lu and Lin, 2025; Zhang et al., 2025) and AI capital⁴ (Drydakis, 2024; 2025). This is useful for exploring the literature since, due to the recency of AI literacy's development, it may not have reached ubiquity – closely related concepts have been explored as well.

Most conceptualisations arise from the field of computer science or digital education (Zhang, Prasad and Schroeder, 2025). Long and Magerko (2020) presented a list of 17 competencies for AI literacy, which will be discussed at greater length in Section 3, but it is worth noting that among these are knowledge of “Programmability”, “Sensors” and “Data Literacy”, similarly suggesting a computing focus. Due to the emphasis on AI literacy for computing, the following sections will also explore the relevance of their popular definition in assessing the suitability of candidates for doctoral level AI programmes in the UK.

2.1. AI Literacy Development

AI literacy does not develop automatically. Instead, a series of institutional and psychological filters govern its trajectory. These filters determine who persists and who leaves the learning

¹ Defined at length by Bawden (2008) as a set of understandings, skills, and attitudes enabling individuals to locate, understand, create, evaluate, and communicate information using digital technologies.

² UNESCO (*Information Literacy*, n.d.) states that “Media and Information Literacy provides a set of essential skills to address the challenges of the 21st century including the proliferation of mis- and disinformation and hate speech, the decline of trust in media and digital innovations notably (AI)”.

³ AI self-efficacy is “Learners’ competence to complete AI practices independently” (Chen et al., 2024).

pipeline.

Institutional structures limit who can progress from basic AI exposure to advanced AI research through technical entry requirements and rigid prerequisites. Among those who enter AI learning pathways, learners decide whether to continue based on two considerations. They judge whether AI is worth pursuing in relation to their goals, and they assess whether they believe they can succeed. These judgments of value and self-efficacy shape decisions to persist or withdraw. Understanding these interactions reveals the specific points where the journey toward expertise stops.

2.1.1. Institutional Access and Technical Gatekeeping

Although definitions of AI literacy do not require learners to possess programming skills or a prior computing background, doctoral study in AI globally continues to carry implicit expectations of technical preparedness.

In the UK, EPSRC-funded Centres for Doctoral Training (CDTs) have broadened access to AI doctoral study to some extent by recruiting applicants without formal backgrounds in AI or computer science. However, research shows that students from non-computing backgrounds and other underrepresented groups begin to experience sustained attrition at much earlier stages of the educational trajectory, giving rise to a pronounced “leaky pipeline”⁵ effect well before doctoral training begins (Sarraj et al., 2023). At the undergraduate level, beyond the formal admission requirements, AI courses often require extended sequences of technical and mathematical training, which delay students’ initial exposure to AI and reinforce entry barriers for non-technical learners (Niousha et al., 2024; Xia et al., 2024).

In sum, institutional access and technical prerequisites act as the initial gatekeepers that define who can begin the journey toward advanced AI research.

2.1.2. Value Perception as a Motivational Filter

Once learners pass the initial institutional gate, value perception operates as a motivational filter that shapes whether learners remain engaged long enough for AI literacy to develop.

Research based on Expectancy–Value Theory and the Theory of Planned Behaviour shows that learners’ engagement with AI is driven more by perceived utility and relevance than by technical exposure alone (Yin & Goh, 2024). When AI is presented primarily as a mathematical or engineering discipline, this framing can weaken the formation of professional identity for students seeking socially oriented roles (Chun and Elkins, 2023). For example, students from underrepresented groups (URGs) often seek socially oriented applications of AI, such as social justice, healthcare, or law. When AI is framed mainly as a technical field, computing can appear socially irrelevant, leading to disengagement (Barretto et al., 2021).

2.1.3. AI Self-Efficacy as a Psychological Boundary

In addition to institutional access and motivational factors, learners’ confidence in their own ability plays an important role in shaping continued engagement with AI learning.

Many novice learners report early intimidation, as they think AI literacy is often perceived as closely associated with programming expertise. AI is frequently perceived through stereotypes that portray the field as highly technical, competitive, and socially isolated, and as accessible mainly to those with prior experience or particular identity characteristics (e.g., White, Asian, man, genius) (Barker, Garvin-Doxas and Jackson, 2002; Beyer, 2014; Cheryan et al., 2013; Lewis, Anderson and Yasuhara, 2016). Cowit and Fiesler (2024) show that such perceptions are associated with persistent uncertainty and self-doubt. Lower self-efficacy is, in turn, linked to earlier disengagement, often before sustained engagement with AI learning occurs. These confidence-related challenges are particularly evident among URGs and women. For URGs, limited exposure to professional role models and a lack of diverse representation in mainstream media can reduce familiarity with the field and increase self-doubt at entry. In addition, the dominant image of the “tech geek” weakens female students’ sense of belonging and interest in computing, contributing to higher attrition rates even among academically high-performing women (Cheryan et al., 2013).

Taken together, these institutional, motivational, and psychological barriers suggest that unequal progression toward advanced AI literacy is not a matter of individual ability, but of

structured access and support.

2.2. Intervention Design

AI literacy has a positive effect on career intention and interest (Zhang et al., 2025a); the positive influence of AI literacy on digital entrepreneurship (Duong, 2025) and software development (Chen et al., 2024) have been measured in exploratory studies of university students in Viet Nam and Taiwan respectively.

Evaluative literature in HE or pre-HE contexts tends to focus either on improving career interest, or on improving participants' AI literacy itself. To understand how AI literacy can be developed in participants and how interest in applying for doctoral studies in AI increases, interventions related to both parts are useful.

2.2.1 Enhancing AI Career Interest

In an umbrella review, Zhang, Prasad and Schroeder (2025) found that only one of 17 reviews focused on HE and adult education – compared with exploratory research, there is little documentation available on evaluative studies for HE learners. This has likely driven the need to increase uptake of university students entering AI courses at undergraduate level rather than postgraduate level, as indicated in global reports on AI education (Mendigutxia, 2024; Maslej, 2025).

In studies aiming to improve career prospects or uptake of AI-related study, AI literacy is rarely named as an outcome. Nevertheless, some such interventions implicitly target AI literacy competencies, so the intervention's relevance can be assessed by mapping the reported activities onto Long and Magerko's (2020) 17 AI literacy competencies and 14 design considerations (listed in Figures 1a and 1b):

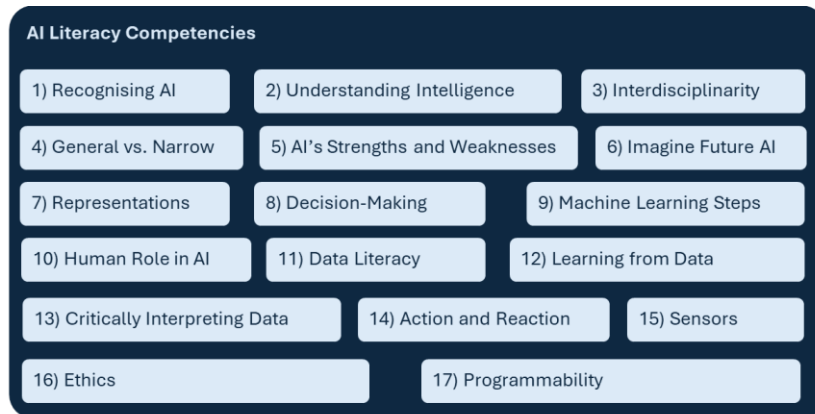


Figure 1a) The 17 competencies of AI literacy as described by Long and Magerko (2020).



Figure 1b) The 14 design considerations for activities to improve AI literacy as described by Long and Magerko (2020).

Oskotsky et al. (2022) report on an introductory AI programme for female pre-biomedicine students to promote diversity in AI careers. It included discipline-relevant programming projects, lecture content, and community-building activities led by diverse faculty. Mapping the intervention components to AI literacy competencies (as seen in Figure 2) suggests that participants were afforded opportunities to develop this skill, though the absence of an explicit measurement of AI literacy limits conclusions about intervention efficacy. Further, while the authors report increases in students' AI knowledge and awareness of diversity issues, the mechanisms underlying these changes are not examined.



Figure 2: The AI literacy competencies which relate to intended outcomes from Oskotsky et al.’s (2022) intervention with female Biomedical students from high schools in California.

With the intention of increasing participants’ AI literacy, Hopson et al. (2025) conducted a quasi-experimental evaluation of an extracurricular intervention with undergraduate pre-medical students. It followed a 4-week mini-curriculum which “integrated foundational AI concepts, ethical frameworks, hands-on engagement with (relevant medical image analysis techniques), and exposure to current AI research”. These activities were successful according to the pre- and post-test results for their 16-item survey, though neither this instrument nor the programme design are directly derived from Long and Magerko’s (2020) framework. Because of this, it is challenging to compare the AI literacy gains of students with other interventions – thus reinforcing the need for a standard tool as also highlighted by Zhang, Prasad and Schroeder (2025).

Together, these studies exemplify the gaps with previous interventions; firstly, that either AI literacy or career interest intend to be improved; secondly, that despite the popularity of Long and Magerko’s (2020) definition, measures of AI literacy are still not consistent.

Because of these factors, using an existing instrument to measure AI literacy which is aligned with the popular conceptualisation will create robust evaluative research whose results are transferrable. Though further content validity, reliability and cross-cultural validity testing would be required, according to Zhang, Prasad and Schroeder (2025), another measure aligned with the above framework is the 31-item scale by Hornberger, Bewersdorff and Nerdel (2023). Alternatively, Laupichler et al.’s (2023) Scale for the assessment of non-

experts' AI literacy (SNAIL) would be most appropriate for evaluating an intervention group comprising students from outside of computer science.

2.2.2 Barriers to Attendance

With this project intending to remove barriers to PhD studies in AI, it is paramount that the intervention itself is accessible and equitable. The inability of members of the target group to access training will diminish the intervention's efficacy.

The digital divide, defined as "a division between people who have access and use of digital media and those who do not" (van Dijk, 2001, p.1) is the most significant barrier to the AI literacy development of school age pupils in the UK (*AI in schools and colleges: what you need to know*, 2025). Despite this, the variability of internet access among UK university students is not well documented. So, it is advisable to implement hybrid engagement modes as a precaution, as is the case for UNESCO's Pre-AI initiative which comprises in-person and online training programmes as well as Massive Open Online Courses (*Prep-AI: Preparing policy-makers and educators for AI and inclusive digital transformation*, 2025). This also facilitates the attendance of others who require this flexibility such as some disabled students or those with caring responsibilities (Zhang et al., 2025b).

2.3 Conclusion and Recommendations

Given that participants' engagement with AI learning is cyclically enabled by their AI literacy and self-efficacy, and that AI literacy increases career interest, this concept is a useful focus for the design of this training. From this section, the following hypothesis is presented for the intervention's evaluation:

H1: Participants' AI literacy increases as a result of attending the training programme.

The evaluative research in prior research is largely inconsistent with the prevailing definition for AI literacy (Long and Magerko, 2020), but following this comprehensive framework for both designing the programme and evaluating its efficacy aligns with recent recommendations (Zhang, Prasad and Schroeder, 2025). The intervention itself needs to be

suitable for its intended participants, and to this end the uncertainty of digital access among university students has been highlighted as an important design consideration.

Providing a down-selection of suitable participant groups at the University of Bristol, the remaining section of this literature review explores how eligibility requirements present barriers, identifying the most salient beneficiary groups.

3. Structural Barriers

The motivation for undertaking the policy analysis stems from the increasing influence of Artificial Intelligence (AI) in the Higher Education (HE) sector, intertwining with broader socio-economic conditions that affect access and doctoral education more generally. First, we review the literature on AI use in the HE context, which we believe has an early influence on students' broader use of AI. Second, we outline key socioeconomic conditions that prevent students from pursuing PhD pathways. Finally, we produced an exploratory analysis of PhD job advertisements to further conceptualise the fragmentation of AI policy and expose some of the structural barriers to AI PhD pathways.

3.1. Shaping AI use on campus – global and UK perspective

The literature on policy and AI in the HE context focuses primarily on how universities govern the use of AI within their institutions. The available literature offers comparative insights into international and local policies.

Globally, a comparative analysis of 343 universities in Australia, Canada, China, the UK, and the US reveals a patchwork of AI policies ranging from permissive instructor discretion to outright bans, with academic misconduct cited as the primary rationale for opposing AI use. At the same time, universities often lack a clear explanation or support resources (Parker *et al.*, 2025). Similarly, a study of 10 AI policies across US institutions

uncovers multilevel governance with varying levels of responsibility, supporting the aforementioned fragmentation of AI policy (Wu, Zhang and Carroll, 2024). The researchers highlight that the ambiguous AI policy and guidance at universities might, in fact, support the characteristics of academic enquiry, allowing students and staff to improve AI literacy and raise awareness of responsible AI use among communities, rather than policing its use.

The fragmentation of AI policy in HE is also highlighted in the UK Russell Group study (Atkinson-Toal and Guo, 2024). Researchers found that institutions employ a wide variety of approaches to determine what is permitted in the use of generative AI in learning and assessment. Although the unacknowledged use of AI typically leads to contract cheating and academic misconduct, the acceptance of AI use varies considerably across UK universities (Table 1). The provision of guidance materials also varies across institutions, with some offering no practical support. The authors Atkinson - Toal and Guo (2024) also emphasise that such a divide in the provision of AI skills may create risks of a digital divide in technology adoption and call for standardised core policy elements to ensure equal and supportive access to AI for students in the UK.

Policy Dimension	Russell Group Principles	University of Bristol (Our Focus)	University College London (The "Progressive" Model)	University of Oxford (The "Traditional" Model)
AI Literacy	Mandate: Universities <i>must</i> support students/staff to become AI-literate, balancing opportunities	Approach: "Foundational." Focuses on long-term skills but warns against "learning loss" and replacing intellectual rigour.	Approach: "Core Competency." explicitly treats AI proficiency as a required future	Approach: "Cautious Engagement." Focuses on the limitations

	with ethical risks.		workforce skill. Heavy emphasis on <i>how</i> to prompt and iterate.	and risks of AI. Literacy is defined by understanding what AI <i>cannot</i> do (hallucinations/bias).
Staff Guidance	Mandate: Departments should apply institution-wide policies to their specific context.	Approach: "Co-Pilot Model." Staff use AI to sense-check and guide. Strong emphasis that AI cannot replace core disciplinary concepts.	Approach: "Designer Model." Staff are tasked with redesigning assessment specifically to either embrace or exclude AI.	Approach: "Gatekeeper Model." Tutors define strict boundaries. Emphasis on Socratic defence (Vivas) to verify student knowledge outside of AI.
Assessment Categories	Mandate: Assessment must ensure "equal access" and	Approach: "Transparency & Trust." Students must disclose <i>why</i> and <i>when</i> AI was used.	Approach: "The Three-Tier System." Assessments are	Approach: "Prohibited unless specified."

	fairness regarding paid tools.	Links policy to EDI/Decolonisation goals regarding bias.	explicitly labelled: 1. AI-Banned 2. AI-Assisted 3. AI-Integral (Required).	The default stance is restriction. AI is generally treated similarly to third-party authorship unless explicitly allowed.
Academic Integrity	Mandate: Policies must be clear; students should not fear penalisation for discussing AI challenges.	Approach: "Student Agency." AI is permitted only when it does not diminish the student's capacity to derive meaning. It lacks "innate intelligence."	Approach: "Acknowledgement." Focus is on proper citation. If you use it, you must declare the prompt and the output trail.	Approach: "Authorship Definition." AI cannot be an author. Submitting work generated by AI as one's own is treated strictly as plagiarism.
Institutional Context	Context: The 24 leading UK	Context: "AI University of the Year." Heavy	Context: London-based, tech-	Context: Historic

	research universities.	investment in Isambard-AI creates pressure to lead technically while managing pedagogical risk.	forward. Positions itself as an innovator in assessment design.	prestige. Prioritizes the "human element" of tutorial- based teaching and original thought above tool usage.
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Table 1: The Fragmentation of National Standards. This comparison illustrates how the broad mandates of the Russell Group are interpreted differently at the local level, resulting in distinct governance models ranging from "Co-Pilot" support (Bristol) to "Gatekeeper" restrictions (Oxford).

The influence of such fragmentation on institutional AI guidelines is reflected in studies that measure students' perceptions and awareness. In a survey by Jiang and colleagues, approximately 79% of students (124 undergraduates) reported the presence of AI policies and restrictions in their classes, but only 48% found these policies clear. Institutional-level guidance was even less recognised (48%), indicating ambiguity and inconsistency (Jiang et al., 2025). They also reported that students who used AI tools for writing or exam support reported greater awareness of AI's limitations, suggesting that active engagement with AI promotes critical understanding. In another study measuring perceptions of AI governance, students prioritised curriculum integration, ethical guidance, misuse detection and fair academic sanctions for unacknowledged use of AI in assessment (Barus et al., 2025).

3.2. Conditions beyond AI Policies

While the AI use policies in HE shape the academic practices and those of doctoral researchers, they do not operate in isolation. As the literature review section on socio-economic barriers explains, there are wider structural barriers stemming from the broader

STEM disciplines. The research of Russel Group Universities found minimal support for EDI and other accessibility factors within policy provisions (Atkinson-Toal and Guo, 2024). Most universities acknowledge AI's inclusive potential but focus instead on copyright and intellectual property risks. Notable exceptions included the University of Oxford's explicit recognition of AI's benefits for users with disabilities, the University of Sheffield's attention to environmental impacts and a RAISE framework, from Queen's University Belfast, which explicitly foregrounded equitable access to AI.

At the University of Bristol, the Centre for Doctoral Training in Interactive AI explicitly embeds EDI discussions in its curriculum, including content on demographic bias in AI systems, democratisation of AI technologies, and inclusive design of AI tools. However, this is specific to that programme rather than the institutional EDI policy itself (University of Bristol CDT Interactive AI, n.d.).

Other factors relevant to this policy context include finance and the national migration and work visa rules. The financial cost of completing a PhD is one of the most significant barriers to postgraduate research (UCL Doctoral School, 2020), with typical fees for home students at the University of Bristol ranging from at least £20,000 for a four-year PhD programme. Fees for overseas students are, of course, substantially higher. A study of postgraduate students at the University of Bristol in the 2022/23 academic year found that 79% of PGRs reported a need for supplementary income, with 82% citing the need to cover essential living costs (Smith et al., 2023)

Finally, the same report found that 86.5% of the international PGRs experience some form of hidden costs, in the form of visa costs, National Health Service (NHS), access to educational resources, health insurance, or other miscellaneous costs.

3.2.1. University of Bristol AI position

University of Bristol has been named the UK's AI University of the Year in 2024. Such a position necessitates an encompassing strategy for inclusion of various expertise, schools and faculties and, as a research-intensive institution, a growing number of research staff, including PhD programmes, to drive its position forward. In this

section, we provide an overview of Bristol University’s AI policy for students, following the Atkinson-Toal and Guo (2024) study of the Russel Group Universities. We used the same approach to analyse the content of the digital document: “Chan (2023) proposed that effective AI policy requires three key considerations for effective management and practical integration: (1) pedagogical to improve learning and teaching; (2) governance to address privacy and security concerns; and (3) operational considerations regarding training, accessibility, and integration.”

Area	Key Points	Details
Pedagogical (Improving Learning & Teaching)	Integration of AI for learning support	AI allowed for <i>general revision</i> , planning, and understanding unit content. Students can use LLMs to generate study plans using Unit Aims, ILOs, covered topics, and timelines.
	Developing critical AI literacy	Policy emphasises factchecking, awareness of hallucinations, and critical engagement with AI-generated outputs. Students are encouraged to use AI tools to enhance understanding, not to replace academic thinking.
	Maintaining academic integrity and learning outcomes	AI should not undermine ILOs or degree classification standards. Writing or paraphrasing by AI for assessments is considered contract cheating. Grammar and spelling checks are permitted.
	Support for better AI use	Examples of recommended prompts are provided to help students generate more informed, critical results from LLMs.
Governance (Privacy,	Consistent but flexible	University-wide policy focused on LLMs, but module leaders may define their own assessment-specific AI

Security & Academic Integrity)	institutional policy	guidance.
	Academic integrity and misconduct	Students must <i>acknowledge AI use</i> in assessments. AI-generated text without disclosure can constitute academic misconduct.
	AI errors and risks	The policy highlights hallucinations, errors, and the need for verification. Promotes responsible and informed use of AI.
	AI detection limitations	Turnitin's AI detection is allowed but considered unreliable. Staff are cautioned about false positives and accuracy issues.
	Guidance for ethical use in research	University neither bans nor promotes unrestricted use; encourages critical engagement while maintaining ethical standards.
Operational (Training, Accessibility & Integration)	Guidance and training resources	Direct links to citation support (e.g., Cite Them Right, librarians). Helps students and staff navigate referencing AI correctly.
	Staff support	Staff receive their own AI guidance to manage detection tools, assessment design, and marking support.
	Integration into learning workflows	AI tools framed as assistive companions for studying, revision, and learning processes, rather than substitutes for academic work.
	Accessibility and evolving technology	Policy acknowledges the rapid evolution and availability of AI, promoting engagement while preparing students for a digital future.

Table 2. Summary of the University of Bristol AI policy for students

3.3. The UK PhD Landscape: Primary Analysis of Barriers to Entry

To complement the literature on institutional policy fragmentation, this review incorporates a primary analysis of the current UK doctoral recruitment market. While university policies govern AI use across universities, the practical barriers to entry are most visible in the live marketplace. To capture a "current snapshot" of these barriers, data was aggregated in December 2025 from *FindAPhD.com*, representing a census of active opportunities in the UK.

We used a custom web scraping tool to collect a dataset of 1,065 unique listings, employing a broad, single-keyword query (keyword = "ai"). The data was processed using a Natural Language Processing (NLP) pipeline⁴:

- **Inclusion Criteria:** No filters were applied regarding funding or location to ensure the inclusion of unfunded positions and interdisciplinary projects.
- **Text Normalisation:** Listings were cleaned of domain-specific "stop words" (e.g., "candidate," "project") to isolate semantic value.
- **Tokenisation:** Text was broken into Bigrams and Trigrams to distinguish specific technical competencies (e.g., "Computer Vision") from general concepts.

We have identified three emerging themes from the data. The first theme concerns socio-economic and financial data; the second addresses limitations of visa sponsorship; and, finally, we discuss a broad theme related to project orientations.

3.3.1. Financial Accessibility and Socio-Economic Stratification

The analysis reveals a resource-dependent entry model, mirroring the "digital divide" concerns highlighted by Atkinson-Toal and Guo (2024). While the majority of the market appears accessible, with **76.9% (819 listings)** classified as funded studentships, a significant minority of **23.1% (246 listings)** remain self-funded or unfunded.

This quarter of the market poses a significant financial barrier, effectively segregating access

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to AI specialisation by personal financial means. This stands in sharp contrast to the inclusive language found in some self-funded listings, such as a project on 'Small Language Models' at the University of Aberdeen: *"We encourage applications from all backgrounds and communities, and are committed to having a diverse, inclusive team."* (FindAPhD.com, 2025)

Despite the statement of encouragement, the position remains structurally accessible only to candidates with sufficient personal capital to cover tuition and living costs. This dynamic risks reinforcing socio-economic disparities, limiting access to advanced AI credentials.

3.3.2. Global Ambition, National Restriction

The fragmentation between institutional ambition and national regulation is most evident in the eligibility criteria. The data indicate a high degree of advertised openness. **79.2% (649)** of funded projects are available to students worldwide, whilst only **20.8% (170)** are explicitly restricted to UK/EU residents.



Figure 1: Frequency Analysis of Multi-Word Terms (N-Grams) Ranked count of the most frequent Bigrams (2-word phrases) and Trigrams (3-word phrases) in the dataset.

However, this apparent accessibility highlights a misalignment. While nearly 80% of roles invite global applicants, this contrasts sharply with the strict costs of the UK visa regime and the typical 30% cap on international recruits within UKRI-funded cohorts. This suggests a "false hope" barrier: the number of eligible international candidates invited to apply far

exceeds the structurally limited number of visa-sponsored positions.

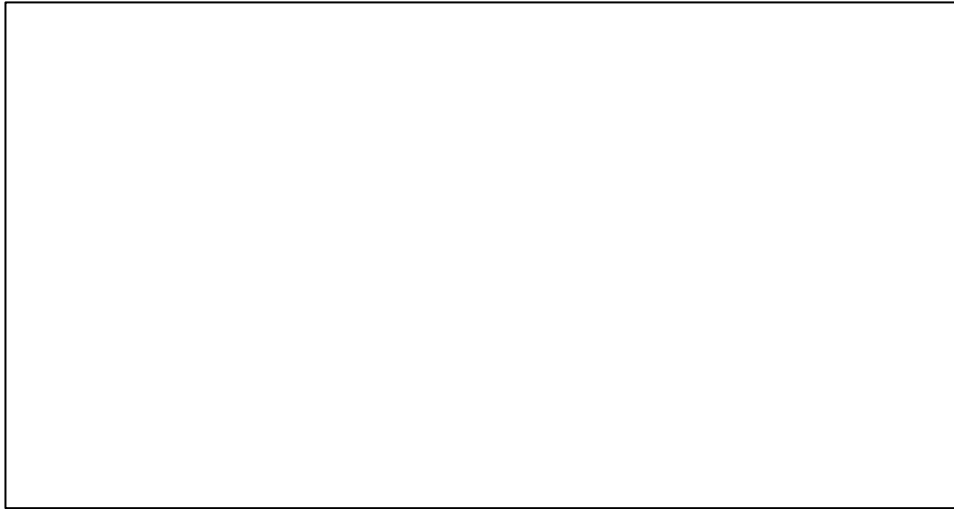


Figure 2: Visualisation of the 100 most frequent terms extracted from the full text of 1,065 UK AI PhD advertisements. Word size indicates relative frequency. Colours indicate semantic clusters: **Blue** represents Technical/Research terms (e.g., Data, Model, Machine); **Red** represents Administrative/Position terms (e.g., PhD, Studentship, Programme); **Green** represents Candidate Attributes (e.g., Experience, Background, Interest).

3.3.3. Estimating Types of AI Projects

To validate the relevance of the dataset and assess the extent to which the listings were genuinely "AI-related," an audit was conducted on a random sample of 100 listings. This process was undertaken to verify the accuracy of the keyword search strategy and to categorise the specific nature of the research being funded.

The classification methodology is presented as follows : to ensure a consistent and reproducible audit of the random sample, a Large Language Model (LLM) was employed to categorise listings based on their project titles and descriptions. The model was provided with a strict classification schema and instructed to assess the primary research intent of each listing. The prompt used is listed in Appendix A. The following categories were used. The lowest confidence predictions were manually verified for accuracy.⁵

- **Category A: Core AI (16%)** - Research focused on the fundamental development of Artificial Intelligence, including model architecture, hardware optimisation, and AI safety.
- **Category B: Applied AI (53%)** - Projects focused on solving domain-specific problems

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(e.g., in Healthcare, Engineering, or Climate Science) using AI as a methodological tool.

- **Category C: Policy & Ethics (8%)** - Studies focused on the societal, legal, or ethical implications of Artificial Intelligence.
- **Category D: Tangential / Non-Core (23%)** - Listings captured by the search query (due to keywords like "Smart" or "Data") where AI was a peripheral element rather than the central research focus.

Category	Description of Research Focus	Count	Funded %	Self-Funded %
Applied AI	Application of AI tools to domain-specific problems.	53	74%	26%
Tangential	Projects where AI is present but not the primary focus.	23	74%	26%
Core AI	Fundamental research into AI architecture/safety.	16	75%	25%
Policy & Ethics	Societal, legal, and governance studies of AI.	8	75%	25%

Table 3: Number and funding status of PhD project types in the 100 randomly sampled PhD listings from our dataset

The distribution data in Table 3 highlights a market heavily skewed toward deployment rather than foundational innovation or governance. With Applied AI (Category B) accounting for 53% of the sample, the doctoral landscape primarily functions as an engine for interdisciplinary adoption - applying existing architectures to domains such as healthcare and engineering - rather than advancing the state of the art in AI itself (Category A, 16%). Notably, research into Policy & Ethics (Category C) remains a niche at just 8%, suggesting that while the UK is rapidly scaling the application of AI, there is significantly less investment in the critical frameworks required to ensure its safety and societal alignment.

We further analysed these categories to determine whether funding availability varied significantly across types of AI research—for example, whether "Core" technical research was more likely to be funded than "Policy" or "Applied" work. However, the analysis revealed a remarkably uniform distribution of financial support at approximately 75%

funded. This reveals that funding seems to be independent of the application area of AI. In this analysis, we cannot compare AI PhDs with non-AI PhDs because we lack complete listing data from FindAPhD.com.

-Method goes here-

*** Disclaimer: Use of AI (ChatGPT, Undermind, Google’s AI-powered literature search tools) to:**

Authors used AI tool to summarise their spoken reflections; form the structure of the second section which was adapted through discussion; identify some relevant literature and pioneers in the field; locate relevant publications, obtain Harvard referencing guidance, and polish the final version to address different writing styles.

Each of these stages incorporated critical questioning and review by at least one author to ensure that the text accurately reflected the authors’ knowledge, as well as to manually audit prose to be in the authors’ own words.

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Appendix

System Role: You are an academic research analyst specializing in the UK doctoral landscape.

Objective: Review the provided list of PhD project listings and classify each one into one of four mutually exclusive categories based on its primary research focus.

Classification Categories:

- **Category A: Core AI:** Research into the fundamental advancement of AI itself. Includes model architecture, hardware optimization, algorithm development, and AI safety/interpretability.
- **Category B: Applied AI:** Projects focused on solving domain-specific problems (e.g., in Health, Climate, Engineering, Finance) using AI as a methodological tool. The innovation lies in the *application*, not the *algorithm*.
- **Category C: Policy & Ethics:** Non-technical research focusing on the societal, legal, governance, or ethical implications of Artificial Intelligence.
- **Category D: Tangential / Non-Core:** Listings captured by the search query (e.g., containing "Smart" or "Data") where AI is peripheral, generic, or not the central component of the research.

Output Requirements:

- Repeat every title in the provided list.
- Assign a specific Category (A, B, C, or D).
- Assign a **Confidence Score** (0–100%) indicating how clearly the title maps to the category.
- Do this for every title in the below list to ensure accuracy

[100 Listings + description inserted here]

Appendix A. Prompts Used for Listing Classification