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PREPARING FUTURE IRISH WORKFORCE FOR AI: EVALUATING THE AI CURRICULUM FOR POSTGRADUATE PROGRAMS

Master's thesis for obtaining the academic degree

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Abstract

This study examines Irish universities preparation of postgraduate students for an AI-driven workforce. It analyzes curricular level data at UCD, TCD, and DCU using the OECD Skills Framework and matches it against the 8 strands of Ireland's National Ai Policy – "AI – Here for Good" Findings reveal UCD's strong technical focus, TCD's technical strength, and gaps at DCU. Aligning curriculum with labor market needs and Ireland's National AI Strategy is essential for producing adaptable, responsible graduates. This research offers practical insights for policymakers and educators to guide curriculum reforms and strengthen Ireland's leadership in ethical and innovative AI development.

Keywords:

Artificial Intelligence, Higher Education, Curriculum Design, OECD Skills Framework, Sociotechnical Systems Theory, Labor Market Needs, National AI Strategy, Irish Education Systems, Postgraduate Programs, AI Skills Gap, Education Policy, Skill Mapping

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1. Introduction

1.1. Background

Technological innovation is one of the defining forces of the 21st century. By reshaping economies, societies, and educational systems worldwide, the advances in automation, data-driven decision-making, and emerging technologies have significantly altered the nature of work. This has resulted in the emergence of new opportunities while simultaneously introducing challenges related to workforce readiness and social equity. Higher education, particularly at the postgraduate level, plays a critical role in providing graduates with necessary knowledge and skills to succeed in a complex, unpredictable professional environments in the age of AI.

The literature reviews the existing landscape of AI development, the growing consensus on the need to integrate a diverse set of skills into educational programs. These include technical and analytical skills, critical thinking, adaptability, and ethical reasoning. These abilities are now considered essential to navigate the demands of contemporary workplaces. However, there is still a notable gap between policy aspirations and actual curriculum implementation. Furthermore, there is still work to be done on how effectively the current curriculum aligns with national strategies and international frameworks whose goal is to promote inclusive and future-ready talent.

1.2. Purpose & Objective

This study examines how postgraduate programs are designed to address evolving skill demands and societal expectations. Specifically, it explores the extent to which these programs integrate diverse skill domains as defined by OECD in their paper, “Emerging Trends in AI Skill Demand Across 14 OECD Countries” (published in 2023). These include cognitive, technical, social-emotional, and transversal competencies as outlined in frameworks such as the OECD Skills Classification and European policy guidelines.

The objectives of this study are twofold

1. To evaluate if there is alignment between Irish postgraduate program curriculum with contemporary skill needs as defined by the National AI Strategy.
2. To offer recommendations for enhancing curriculum design and policy coherence.

The rationale behind this research lies in the need to prepare future graduates not just as specialists but as adaptable, ethically aware, and socially responsible professionals who can contribute meaningfully to rapidly evolving societal contexts. With these objectives, the study will add to the ongoing discourse on educational reform by documenting innovation in postgraduate education.

Methodologically, this research employs a qualitative content analysis of postgraduate program curricula from leading Irish universities (UCD, TCD and DCU), complemented by a mapping exercise using the OECD-based AI Skill Taxonomy as an evaluation framework. By systematically analyzing program structures and course modules, the study generates insights into the strengths and shortcomings of current educational offerings in Irish postgraduate curriculum.

The structure of this thesis has the following theme. The next chapter presents a literature review that combines existing research and situates this study within broader academic and policy discussions. This is followed by the methodology chapter, which outlines the data sources, analytical approaches, and evaluation criteria employed. The results chapter provides an in-depth presentation of the findings, while the discussion chapter interprets these results in light of theoretical frameworks and policy implications. The final chapter provides a conclusion to the research by summarizing key contributions, suggesting recommendations and directions for future research.

By situating this deep dive within current educational, economic, and social debates, this thesis aims to advance understanding of how postgraduate programs can be more effectively designed to meet the needs of both graduates and the societies they will serve.

1.3. Research Questions

Over the course of the research, the questions have been carefully refined from a broader focus to a much more specific one - That is, how higher education institutions (HEIs) in Ireland are preparing students for the evolving workplace through their postgraduate programs.

1. Research Question 1 - How are higher education institutions (HEIs) in Ireland addressing and incorporating workplace-relevant AI skills into their postgraduate education programs?
2. Research Question 2 - How closely does the selected HEIs course design align with the Key Strands of the National AI Policy of Ireland?

1.4. Hypothesis

Since the study Based on this Study, the key hypothesis was developed as follows:

1. Hypothesis 1 - Irish Higher Education Institutes curriculum has partial alignment with the Top 20 AI Technical Skills Defined by OECD.
2. Hypothesis 2 - Ireland's HEI curriculum aligns has a high alignment with OECD AI Skills Cluster, which are reflected in Ireland's National AI Policy Strands.

1.5. Scope of the Study

This study looks at postgraduate courses offered by three universities in Ireland: University College Dublin (UCD), Trinity College Dublin (TCD), and Dublin City University (DCU). It focuses on full-time postgraduate programs leading to a master's degree, and those under the umbrella of artificial intelligence (AI), through their titles or the descriptions of the modules they offer. The research examines the design of the programs themselves, rather than tracking the outcomes for graduates or how the courses affect the job market. The goal is to explore how well these courses reflect the kinds of skills that are considered important for working with AI today. To do this, the study uses two frameworks developed by the OECD: one for general AI-related skills and another for technical AI skills. This is accomplished by comparing course content to these frameworks using keyword analysis, correlation tests, and other tools. The research shows how these universities are preparing students for the growing role of AI in the workplace through their course curriculum. Keeping the focus on curriculum makes the study more manageable and allows it to rely on information that's publicly available.

1.6. Relevance of the Research

This research investigates how a selected sample of Irish education institutions are preparing postgraduate students with skills relevant to an AI-driven economy. As artificial intelligence becomes more entrenched in the workplace and public life, the ability to understand, apply, and evaluate AI technologies is increasingly important. The study assesses how AI-related skills are reflected in the curriculum of the selected Irish universities. Using the OECD's AI Skills Framework as a reference point, the analysis examines how much the existing course content matches with internationally recognized skill categories such as machine learning, data analytics, algorithmic transparency, etc. This alignment is especially important in the context of Ireland's National AI Strategy, which identifies education and talent development as one of its core pillars. By comparing institutions individually and collectively, the research highlights the extent to which current academic programs support the national goal of nurturing responsible and inclusive AI adoption. The results provide a foundation for curriculum review, institutional planning, and broader policy discussions on preparing graduates for the evolving demands of the digital economy.

2. Literature Review

2.1. Introduction

New technologies entering the labor market introduces new opportunities and threats. They create demands for new occupations and evolve the function of existing roles, as they improve productivity and standards of living (Autor et al., 2024, p. 4). Artificial Intelligence (AI) is emerging to be the great disruptor of the 21st century. The technology has the capability to speed up scientific research and aid solutions in critical problems surrounding healthcare and climate change (Siala & Wang, 2022). Therefore, it is important to study and understand the trickle-down effect and the distributional consequences of such changes, as it provides policymakers a roadmap to design appropriate education and skills policies (Webb, 2019, p. 2).

Artificial intelligence is continuously restructuring the global economy, employment patterns, and education systems worldwide. As a result, the demand for AI-relevant competencies has risen sharply. In order to keep up with the changes, nations are reforming their policies (tech, education, public services, etc) to better suit the evolving labor market needs.

Brynjolfsson and McAfee (2014) break down the technological advances in their book 'The Second Machine Age'. First, they analyze the contemporary period characterized by rapid technological advancement, predominantly in the field of artificial intelligence (Spencer, 2017). According to their analysis, AI is predicted to become commonplace in different sectors, including healthcare, law, finance, and logistics. If we go back even further, Frey and Osborne (2013) also assessed that nearly half of U.S. jobs were at increased risk of automation or replacement by AI, however this analysis is contradicted by newer studies that present reduced numbers (Kande & Sonmez, 2020). Yet, the common consensus is that AI will displace routine tasks while evolving and creating new roles requiring advanced digital, analytical, and interpersonal skills (Arntz et al., 2017; Chui & Manyika, 2016).

There is limited evidence on how higher education institutions (HEIs), especially at the postgraduate level, are responding to the talent and skills requirements of an AI-driven economy. The evolution of AI shines a light on the importance of flexible educational frameworks capable of preparing a workforce with a learning mindset, and cross-disciplinary knowledge (Walter, 2024). The study of such changes helps individuals to choose career paths that are best suited to their skill sets, while at the same time preparing them to enter the labor market.

2.2. Historical Evolution of AI and Its Impact on the Global Labor Market

Examining the history of Artificial Intelligence (AI), it is noted that its development dates back to the mid-20th century. Closely linked to advances in computing and mathematical modeling, Alan Turing's groundbreaking work on the subject in the 1950s laid the foundation for machine-based problem-solving (Furtado, 2018). Early attempts at natural language processing using symbolic systems, AI started gaining momentum in the 1960s and 1970s, although technological limitations limited its progress. Spearheaded by expert systems and improved computational capacity in the 1980s and 1990s led to the resurgence of AI, creating applications in finance, engineering, and medical diagnostics (Dwivedi et al., 2021).

Improvements in computing power and focus on cognitive science and constructivist learning theories also introduced AI in education, with systems such as ANDES and AutoTutor that incorporated natural language processing and dialogue systems facilitating a more interactive learning environment in academia (Burton, 2024; Smith-Mutegi et al., 2025a). These tools made the transition from programmed instruction to adaptive systems capable of mimicking human tutoring behaviors easier.

In the 2010s, the conjunction of cloud computing, big data, and advanced machine learning techniques (particularly deep learning) provided breakthroughs in AI technology. They made way for new applications in image recognition, autonomous vehicles, real-time language translation, production, and service delivery, among others (Dean, 2022). Brynjolfsson and McAfee (2014) maintain that since then, AI morphed into a general-purpose technology, comparable to how electricity or the internet reshaped the economic landscape (Agrawal et al., 2019). Such advancements introduced personalized learning at scale with platforms like Coursera, Duolingo, and Udemy who integrated AI to provide customized learning experiences, recommend content, and automated assessments (Halkiopoulos & Gkintoni, 2024; Oyebola Olusola Ayeni et al., 2024).

Institutions also started experimenting with AI in higher education for tasks like student advising, administrative automation, and virtual teaching assistants. An example of AI used for such functions is US-based Georgia Tech's Jill Watson, an AI-powered discussion board moderator (Seo et al., 2021).This decade also saw the emergence of AI-powered learning analytics, making institutions capable of collecting and analyzing massive amounts of student data. This adoption supported the growth of predictive models that helped in identifying learning patterns, risks of dropout, and potential performance issues (Sghir et al., 2023). Hence, AI's role evolved from individual pupil support to curriculum optimization and institutional decision-making.

AI's impact on the labor market has followed a similar evolution. Early automation replaced low-skill, routine tasks, whereas modern AI continues to affect middle-skill and white-collar jobs like administrative support, paralegal work, and technical analysis (Bonney et al., 2024). A published report by the World Economic Forum (2020) called "The Future of Jobs Report" estimates that approximately 85 million jobs will be displaced globally by automation by 2025. However, it also estimates the creation of 97 million new roles in the field of AI development, digital transformation, and data analysis (Agrawal et al., 2020).

The digital transformation of education was heavily accelerate by The COVID-19 pandemic. This also revealed the potential and limitations of AI tools. AI supported platforms did facilitate remote learning, automated grading, and real-time student engagement monitoring, but also raised concerns regarding algorithmic bias, data privacy, and digital inequality (Williamson et al., 2020). These developments also create the necessity for reexamining the ethics, governance, and inclusivity of AI in education, and create the need for transparent and accountable systems.

The cumulative effect of AI technology on employment is dependent on the investment by economies and institutions in the upskilling and transitioning of workers for emerging occupations (Acemoglu & Restrepo, 2019; Fornino & Manera, 2022). The speed of AI transformation however, outstrips educational reform. In their cross-national analysis, OECD researchers in their Digital Education Outlook report (OECD 2023) noted that the demand for digital and analytical skills is growing, however, education systems are still catching up to integrating them into formal curricula (Kralj, 2024).

2.3. Theoretical Frameworks for Skill Assessment

Several theoretical frameworks can be used to understand the juncture of education, artificial intelligence, and labor market transformation. These frameworks provide conceptual clarity for analysis purposes, on how educational institutions respond to technological change. They also allow researchers to observe how such responses affect workforce development and social equity.

2.3.1. Human Capital Theory (Becker, 1964)

Human Capital Theory has been widely accepted as the foundational framework in education economics and labor market studies since being introduced by Gary Becker in the 1960s. The theory conceptualizes acquired education and skills as investment in human capital, and resources that enhance individual productivity, innovation potential, and economic contribution (Becker, 1964).

Within the context of AI and education policy, the adoption of Becker’s theory has been validated by economic studies linking technological advancements with rising returns to high level skills (Goldin & Katz, 2010). As AI transforms labor market demands, the OECD Skills Strategy (OECD, 2023) incorporates Human Capital Theory to frame policy recommendations for national upskilling programs and education system reforms. The theory's significance is in its use to support strategic investment in education in supporting productivity, resilience, and inclusive economic growth.

The categorization of essential competencies into cognitive, technical, social-emotional, and transversal domains draws from OECD frameworks defined within the program for the International Assessment of Adult Competencies (PIAAC) and outlined in the OECD Skills Outlooks (Valiente & Lee, 2020). This classification also applies to initiatives like Springboard+ and the Human Capital Initiative in Ireland, which support postgraduate and micro-credential programs in high-demand digital fields. While Human Capital Theory is critiqued by scholars like Marginson (2019) and Wolf (2002) for its narrow economic focus and neglect of education's social aspects, it serves as a rationale for educational responses to technological shifts (Leoni, 2025). Nevertheless, Human Capital Theory plays an important role in framing education as a strategic tool in response to technological advancements.

2.3.2. Technology Acceptance Model (Davis, 1989)

Conceptualized by Fred Davis in 1989, the Technology Acceptance Model (TAM), represents a structured framework for the understanding and adoption of usage trends related to novel technologies by individuals (Kowalska-Pyzalska, 2024). TAM asserts that end users' acceptance of a new technology is determined by two main factors: perceived usefulness (PU) and perceived ease of use (PEOU), which subsequently influence their practical utilization patterns (He et al., 2018).

The theory has also been used in assessing the outlook of students and educators towards AI-powered systems in education. Examples of these systems include automated assessment tools, learning analytics interfaces, intelligent tutoring systems, and virtual learning environments (Ifenthaler & Yau, 2020). It is widely quoted by academics in literature, making it a frequently occurring model in technology adoption frameworks. The theory is preferred for its simplicity, empirical validity, and predictive capability in evaluating the amalgamation of digital tools and platforms in educational frameworks (Jesus et al., 2025).

The Technology Acceptance Model has also been extended into variations, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) (University of Arkansas et al., 2016). This variation builds on the original theory and explores constructs like social influence and facilitating conditions, as it considers them relevant in institutional contexts. The adaptability of this theory increases its adaptability to various scenarios, including organizational and cultural factors influencing technology acceptance in higher education. In summary, TAM provides a solid theoretical basis for analyzing the behavioral and perceptual influences swaying the adoption of AI technologies in postgraduate education.

2.3.3. Sociotechnical Systems Theory (Trist & Bamforth, 1951)

As part of their research at the Tavistock Institute, Eric Trist and Ken Bamforth introduced the Sociotechnical Systems Theory (STS) in 1951. This theory offers a framework for understanding the co-designing of social and technical elements for optimal outcomes in organizational settings. In a first of its kind study of coal mining operations in the UK, both Trist and Bramford demonstrated that isolating technical systems from social context would lead to inefficiencies and worker dissatisfaction, hence underscoring the value of integrated design (Trist & Bamforth, 1951).

For AI integration in education, STS is utilized to explain how the successful implementation of educational technologies depends not only on technological capability but also on alignment with pedagogical goals, faculty practices, institutional culture, and learner diversity (Pasmore, 1988; Bostrom & Heinen, 1977). Contemporary applications of STS in higher education emphasize its role in guiding the development of learning environments where AI tools, including virtual assistants, intelligent tutoring systems, or predictive analytics. It analyzes how AI is embedded in ways that enhance human learning rather than replace it (Sarker, Chatterjee, & Xiao, 2013).

The significance of STS lies in its capacity to address potential tensions between innovation and inclusivity. It offers a theoretical lens through which the introduction of AI in postgraduate education can be examined for its impacts on institutional structures, academic labor, and student experiences (Williamson & Piattoeva, 2021).

2.3.4. Skills-Biased Technological Change (SBTC)

SBTC theory proposes that technological advancements benefit high-skilled workers more, whereas displacing those in routine, middle skilled occupations. This framework explains the labor market polarization and supports the argument for targeted educational interventions (Card & DiNardo, 2002). The theory gained popularity in the 1990s through empirical studies investigate the relationship between computerization and labor market outcomes in the United States (Acemoglu & Restrepo, 2022).

The core premise of SBTC is that advancements in technology increase the output and subsequently, the demand for high-skilled workers, such as those with analytical, cognitive, and problem-solving abilities. At the same time, it reduces the demand for routine-based, middle-skill jobs that can be automated (Halx & Reybold, 2006). As a result, wages for high-skilled workers increases, while those in low and middle-skill occupations face wage stagnation or displacement. This pattern contributes to the well-documented U-shaped effect on employment growth, where high and low skill occupations grow comparative to middle-skill roles (Gould & deCourcy, 2023).

Research conducted by Goos, Manning, and Salomons in the EU context reinforces the SBTC hypothesis by demonstrating how ICT-driven change can cause occupational polarization across European labor markets (Goos et al., 2014). Similarly, the European Centre for the Development of Vocational Training also states that future skill demand will continue to move towards non-routine analytical and interpersonal competencies (European Centre for the Development of Vocational Training, 2022).

2.3.5. Constructivist Learning Theory (Piaget, 1972; Vygotsky, 1978)

The Constructivist Learning Theory is grounded in the work of Jean Piaget and Lev Vygotsky, both of whom emphasized the active role of learners in constructing knowledge via experience, interaction, and reflection. Piaget’s cognitive constructivism explained how individuals developed understanding through stages of cognitive development, while social constructivism by Vygotsky's emphasized the importance of social context, language, and collaboration in learning (Prakash Chand, 2023).

This theory is widely quoted in education research, especially in designing learning environments promoting critical thinking, problem-solving, and experiential engagement. In AI-integrated education, constructivist principles from this theory help adaptive learning platforms, project-based learning, and collaborative virtual environments that tailor instruction to learner needs and encourage active participation (Gligorea et al., 2023).

In postgraduate education, constructivist theory supports curriculum models that support interdisciplinary learning, real-world application, and student agency. These approaches promote transversal and social-emotional skills—such as adaptability, creativity, and collaboration—identified as essential by the OECD (OECD, 2023). Constructivist theory also forms the basis for assessment strategies in AI education, promoting reflective, and performance-based evaluations by valuing student autonomy and contextual learning through the development of lifelong learning competencies and critical digital literacies (Do et al., 2023).

2.3.6. Institutional Theory (Meyer & Rowan, 1977)

Institutional Theory by Meyer and Rowan (1977), proposes that organizations are shaped not only by efficiency goals but by their need to gain legitimacy inside a broader institutional environment. According to this theory, organizations (including universities) comply with rules, norms, and expectations put forward by the regulatory bodies, accreditation agencies, professional associations, and societal values in order to attract resources, stability, and legitimacy.

Institutional Theory can be used to analyze AI education and its capacity to explain the adoption or resistance to curricular innovations such as AI-focused programs. Higher education institutions are not autonomous entities; they operate within environments influenced by national policies, funding structures, and societal discourses on digital transformation. For example, Ireland's National AI Strategy (Government of Ireland, 2021) and the EU Digital Education Action Plan (European Commission, 2020) shape institutional agendas by laying down guidelines for AI capacity-building, ethical standards, and interdisciplinary education. These policies become institutionalized norms influencing program design, staffing, and investment decisions in universities.

DiMaggio and Powell (1983) along with other researchers, have expanded this theory through the concept of isomorphism - mechanisms by which organizations in the same field become increasingly similar over time. Mimetic isomorphism in educational industry happens when institutions adopt similar AI related curricula to appear as their successful peers, while under pressure from professional standards or accreditation criteria for credible AI programs (De Freitas & Da Silveira, 2021). For example, postgraduate AI programs in Irish universities use both national strategies and competitive pressures to create programs that attract international students and research funding. Using this theory can help researchers view the phenomenon through a macro-level lens for understanding how institutional legitimacy can be maintained in an evolving technological landscape.

2.4. Curriculum Design and Theoretical Instruction

Designing an effective curriculum is one of the core concerns in higher education. The curriculum is shaped by educational theories, institutional goals, and the needs of society. Literature reiterates that a strong curriculum design delivers more than education, it thoughtfully organizes learning experiences so that they build on each other and are in harmony with overall program goals (Wang, 2024).

This idea of “constructive alignment” proposes that in order to develop a comprehensive understanding, the expectation to learn, methods used for teaching, and assessment tools and criteria should seamlessly support each other. This is infinitely more important in postgraduate study, where learners are encouraged to think critically, engage in research, and apply their knowledge in practical settings (Hailikari et al., 2022).

Scholars also highlight the need for flexibility and agility in curriculum design. Piaget and Vygotsky focused on active, student-centered learning techniques. Key to this approach is to encourage students to build their own understanding by solving problems, working together, and reflecting on their experiences (Blake & Pope, 2008). Including real-life tasks and opportunities for critical thinking helps students develop skills they can apply beyond the classroom (Halx & Reybold, 2006).

Overall, the literature suggests that a well-designed curriculum, focusing on strong educational principles, helps create programs that are both academically strong and socially relevant.

2.5. Higher Education Curriculum Design and AI Technology

As AI applications in education evolve, higher education institutions are still catching up with the trends by including more AI-related courses into their program curriculums, particularly as a specialization. The impact of AI goes further due to its interdisciplinary nature, as is evident by its relevance in fields such as healthcare, finance, law, and engineering, all of which have a certain level of AI based courses included in their programs (Crompton & Burke, 2023).

According to a global survey conducted by HolonIQ in 2021, more than 70% of top-ranking universities integrated AI or data science modules into postgraduate programs by 2021 (Artificial Intelligence in Education. 2023 Survey Insights). These courses included subjects such as data ethics, neural networks, machine learning, natural language processing, and AI applications in industries.

For Ireland, these global developments in AI are making the government reevaluate workforce preparedness. Ireland is strategically positioned as a hub for global technology firms, which places additional responsibility and pressure on its education system to prepare a workforce capable of supporting AI innovation. The government's emphasis on 'AI talent' in national strategies recognizes the urgency, however evidence from Higher Education Authority reveals persistent gaps in curriculum alignment, access to specialized training, and digital infrastructure (Autor et al., 2024).

The inclusion of AI-related courses in Ireland has witnessed a growing trend over the past few years. The Higher Education Authority (HEA, 2023) reported that most of the major Irish universities are offering M.Sc. programs in AI, Data Science, and related fields (O'Raghallaigh, 2025). For example, University College Dublin (UCD) offers a dedicated M.Sc. programs in Computer Science (AI), Data and Computational Science, and Digital Policy with AI modules. Trinity College Dublin (TCD) offers M.Sc. programs in Intelligent Systems and Future Networked Systems, which incorporates specialized AI coursework.

Despite these integrations, higher education institutes remain challenged in maintaining the depth and breadth of AI coverage in these programs, along with the speed of AI development vs. inclusion in the curriculum. According to a recent audit conducted by Skillnet Ireland (2022) 80% of AI-focused programs covered core technical skills, but only 35% included content on AI ethics, and just 25% covered project-based learning reflecting real-world applications (Bukartaite & Hooper, 2023a). This mismatch reveals the flipside that while students graduate with technical knowledge, they still might not grasp the broader competencies required in applying AI in a responsible and collaborative manner in professional settings.

While the addition of AI-related courses in higher education has improved over the past few years, especially at the postgraduate level, improvements are needed to make sure the curriculum is up to date, interdisciplinary, and aligns with industry standards and societal needs. A balance needs to be achieved between technical, practical and ethical dimensions of AI education, which is essential to equip graduates for leadership roles in an AI-driven world.

2.6. The National AI Strategy: "AI – Here for Good"

Unveiled in 2021, the strategy lays out a comprehensive vision aimed at positioning Ireland globally as a leader in AI development and deployment. It presents a 10-year plan on integrating AI in the core functionalities of business, public service, education, and other functions. A major focus of the strategy is the development of talent pipelines to support AI technology rollout in public and private sectors. The strategy focuses on collaboration between HEIs, government, and industry to develop AI competencies through formal education and lifelong learning initiatives (Department of Enterprise, Trade and Employment, 2021).

This strategy is supported by targeted funding programs such as the Human Capital Initiative (HCI), Springboard+, the Irish Centre for High-End Computing (ICHEC), and the Insight Centre for Data Analytics. However, the strategy's rollout has been uneven, with significant variations in institutional responsiveness and capacity across HEIs (HEA, 2023).

Ireland's National Artificial Intelligence Strategy, details the country's commitment to integrating AI into Irish society and the economy in an inclusive and responsible manner. The document sets a framework to position Ireland as an international leader in applying trustworthy AI, supported by public trust, ethical standards, and human-centric innovation. Ireland's approach clearly aligns with the EU's High-Level Expert Group on AI and the OECD AI Principles, which advocate for AI systems that are accountable, transparent, human-centric, and socially beneficial (Ireland AI Strategy Report - European Commission, n.d.). The strategy's goal is that AI must be understandable, accepted and trusted by the public and urges a societal shift towards informed participation in the AI economy (European Commission. Joint Research Centre., 2022). This emphasizes the importance of not just creating and developing AI technologies, but also nurturing AI literacy, ethical awareness, and inclusive digital citizenship.

This vision is deeply connected to the concept of AI competence outlined by the OECD: AI-readiness is not just technical, it requires capacity-building in communication, interdisciplinary integration, ethics, and domain-specific applications. The national strategy's education agenda mirrors this approach, encouraging institutions to insert AI across disciplines, and to avoid AI knowledge in technical courses alone.

The key strands of the strategy are summarized below:

No.	Strand	Focus Area	Policy Direction	Research/Policy Implication
1	**AI and Society**	Emphasizes public trust, ethical use, and transparency in AI. Supports public engagement and informed discourse;	Ensures that AI is people-centered, inclusive, and aligned with democratic values and human rights.	Supports the OECD's call for interdisciplinary and social impact skills (e.g., public trust, ethics, human rights).
2	**Governance Ecosystem**	Develops legal, ethical, and regulatory mechanisms for the use of AI. Promotes consistency and accountability in AI governance	Provides a strong policy framework for responsible AI development and use, especially around data, ethics, and safety.	Mirrors OECD's emphasis on AI governance literacy, regulatory awareness, and ethical compliance skills.
3	**Enterprise Adoption**	Focuses on building AI literacy at all levels; from schools to industry. Supports reskilling and lifelong learning.	Develop a pipeline of AI talent, upskill the workforce, and integrate AI into mainstream education.	Calls for technical skills aligned with OECD's AI design and deployment capabilities.
4	**AI in Public Services**	Supports strengthening of the AI research, development, and enterprise base across public and private sectors.	Supports investment in AI research, startups, SMEs, and partnerships to build Ireland's competitive edge in the AI economy.	Requires skills in AI applications, data analysis, and ethical procurement frameworks.

5	**AI Innovation Ecosystem**	Positions Ireland as a trusted international partner in AI through EU and global collaboration	Promotes responsible AI globally and aligns Ireland's strategy with international norms, especially EU values and multilateral cooperation.	Emphasizes research skills, testbeds, and collaborative innovation OECD calls this "cross-functional AI proficiency".
6	**Education, Skills, and Talent**	Applies AI to improve public services such as healthcare, education, transport, and public administration.	Encourages innovation in the public sector by leveraging AI for better decision-making, efficiency, and citizen experience.	Directly aligned with the OECD's classification of technical, complementary, and cognitive AI skills.
7	**Infrastructure**	Addresses data availability, technological infrastructure, and cyber systems.	Ensures that the technical foundations for AI like data access, cloud platforms, and broadband, are in place to support innovation.	Tied to AI-enabling infrastructures like high-performance computing, data security, and access to datasets.
8	**Implementation**	Sets up monitoring and accountability mechanisms for the strategy itself. Safeguards cross-departmental coordination	Focuses on timely delivery, progress tracking, and coordination across government bodies and stakeholder communities.	Promotes sustainable skills governance; a key enabler in OECD's AI competency map.

Table 1 – Key strands and summary of Ireland's National AI Policy, "AI: Here for Good".

Core to strand 6, (education, skills and talent) is the recognition that AI readiness requires more than just technical training. The strategy encourages the development of a talent pipeline that is future ready, through investment in education, continuous upskilling, and targeted postgraduate programs. It stresses that Ireland's higher education institutions (HEIs) must integrate AI and data science education across disciplines. This integration should not just be within STEM fields, but also in healthcare, law, business, and the humanities (O Donnell et al., 2024).

A key priority of this strategy is promoting interdisciplinary learning, encouraging curriculums that combine AI with ethics, policy, and human-centered design. Additionally, the strategy promotes collaboration with industry, advocating for joint research centers, experiential learning opportunities, and co-developing postgraduate curriculums to make sure that academic content remains aligned with the evolving labor market. The strategy mirrors EU-wide digital policy initiatives, including the Digital Education Action Plan 2021-2027 and the Coordinated Plan on AI

(2018). This will ensure that Ireland's approach remains competitive and coordinated within the broader European education sector (Gov.ie, 2024).

However, strategy implementation has been sporadic. Although there has been progress, such as the expansion of Springboard+ in 2011 and the launch of several AI postgraduate scholarships, recent reports from the HEA (2023) and Skillnet Ireland (2022) suggest that the speed of curriculum reform and institutional capacity-building lags behind. Major issues highlighted a lack of trained academic staff, insufficient integration of AI ethics modules, and limited support for cross-disciplinary initiatives (Daly, 2025). The strategy's commitment to equity by making sure all students and professionals can engage with AI, regardless of background - requires more active outreach to underrepresented groups and greater investment in digital infrastructure across all regions (Newell, 2024).

2.7. AI Strategies in Other European Countries

Ireland's strategy shares similarities with those of other European nations but has its own unique strengths and weaknesses. Below is a short synopsis of some of the AI strategies across European countries, and their approaches to education and AI.

1. **Finland's AI 4.0 Program** (2020) emphasizes the inclusion of AI education across all levels, including free online micro credentials and vocational upskilling programs, all under the umbrella of the Finnish Ministry of Economic Affairs and Employment. Their model of open-access AI education is helping democratize AI literacy across professions (Moraitis, 2025).
2. **Germany's** government in their most recent proposal **"Artificial Intelligence Action Plan"** (presented in 2023) under their National AI strategy, focuses on integrating AI into research and innovation ecosystems. Their approach is to provide significant federal investment in university-based AI centers of excellence and research (Delcker, 2024).
3. **France's AI for Humanity** (2018) initiative emphasizes public-sector AI ethics and has funded AI research chairs within universities. It also supports interdisciplinary postgraduate programs for AI in social science and humanities contexts, aligning with Ireland's call for cross-disciplinary curriculum reform (France AI Strategy Report - European Commission, 2021).

While Ireland’s focus on trust, inclusion, and alignment with European policy is quite positive, compared to Finland its accessibility and lifelong learning integration is not that established (Lefort, 2023). Ireland also lacks extensive federal research investment like Germany has access to, however, it has made significant progress than many EU counterparts in terms of aligning AI education with national skills strategies (Csernatoni, 2025).

Ireland’s National AI Policy provides a solid foundation for integrating AI education and skill development in the country. However, to truly give themselves a competitive advantage they need to establish sustained funding, cross-sector collaboration, and HEIs to adopt agile, inclusive, and interdisciplinary approaches to curriculum design and delivery, and for embedding AI education and skills development in Ireland (Dooley, 2025).

2.8. Evolving Skill Requirements in the AI Economy

Several studies have identified the transformation in the skills required by employers as per the current labor market trends in the light of AI-adoption. The World Economic Forum (2020) has categorized essential skills into three primary domains. These include the following

1. Technical skills (e.g., AI development, coding, data science).
2. Cognitive skills (e.g., problem-solving and critical thinking)
3. Social-emotional skills (e.g., collaboration, adaptability).

These classifications in skill requirements are a reflection of the fundamental transition of previously task-based roles, to knowledge-intensive, interdisciplinary occupations.

Despite the growth in STEM enrolment, employers feel that graduates are not adequately prepared for AI roles. The main concerns are a lack of practical experience, interdisciplinary thinking, and ethical awareness (Smith-Mutegi et al., 2025b). Skillnet Ireland (2022) and the Expert Group on Future Skills Needs (2021) have reported shortages in AI-related roles, particularly in applied natural language processing, machine learning, and AI ethics (Bukartaite & Hooper, 2023b). It is reasonable to conclude from these reports that although technical training without broader competencies complementing real-world applications is not sufficient.

2.9. The OECD Skills Classification Framework

The OECD's work on skills classification was a response to growing global trends in structural unemployment, fast technological change, and the gap between education systems and labor market needs. In the early 2000s, OECD studies began emphasizing the importance of human capital in economic growth. This resulted in the creation of the Skills Strategy in 2012. This was followed by the Emerging Trends in AI Skill Demand Across 14 OECD Countries report in 2023. The framework's methodology is a process that is in line with OECD's tradition of evidence-informed policymaking, and is a combination of data-driven labor market analysis, expert consultation, policy alignment, and iterative validation (OECD, 2024).The framework is structured around four principal categories of skills: cognitive, technical, social and emotional, and transversal, summarized as follows:

Skill Category	Definition	Examples
Cognitive Skills	High-order mental processes	Reasoning, problem-solving, critical thinking, and decision-making under uncertainty.
Technical Skills	Discipline-specific abilities required to develop or apply AI systems	Programming, data analysis, machine learning, and cloud computing.
Social and Emotional Skills	Interpersonal and intrapersonal skills	Communication, teamwork, leadership, and empathy, supporting collaboration in AI-integrated environments.
Transversal Skills	Broad, cross-cutting skills	Digital literacy, creativity, ethical reasoning, and lifelong learning that apply across jobs and sectors.

Table 2 - Skills Classification Framework, as defined in Emerging Trends in AI Skill Demand Across 14 OECD Countries, Vol 2 (2023)

The OECD Skills Classification Framework also links several theoretical perspectives on economic returns to education (Human Capital Theory), labor market polarization (SBTC), socio technical integration, constructivist pedagogy, technology acceptance, and institutional legitimacy. This theoretical alignment complements the framework's suitability as both a diagnostic and developmental tool for evaluating postgraduate AI curriculum.

As AI technologies proliferate across labour markets globally, the exact classification of AI-related skills has become paramount for forecasting its effects in various areas. These include curriculum design, skill demand, and workforce policy. A key contributor to this classification is the OECD's taxonomy of AI skill clusters. These were described in the 2023 report, "Emerging Trends in AI Skill Demand Across 14 OECD Countries" as part of the OECD Artificial Intelligence Papers (Borgonovi et al., 2023). Based on large-scale job vacancy data, these clusters characterize a structured classification of technical competencies frequently associated with AI job postings across multiple countries (Alekseeva et al., 2021).

The report categorizes AI skills into seven distinct clusters: Machine Learning, Artificial Intelligence (general), Neural Networks, Natural Language Processing, Robotics, Visual Image Recognition, and Autonomous Driving (OECD, 2024a). Each of these are grouped together based on associated technical skills or applications. The methodology used by OECD combines keyword-based AI job classification with skill clustering, suggesting a replicable framework for national studies. It uses Lightcast vacancy data from 51,000 online job boards, identifying AI-related postings through a conservative approach: roles that require at least two generic AI skills (e.g., "machine learning") or one specific skill (e.g., "natural language processing") (OECD, 2023, p. 17.). They are summarized in the table below:

Skill Cluster	Definition / Focus Area
Machine Learning	Techniques aiding computers to learn from data without explicit programming.
Artificial Intelligence (general)	Broad category foundational AI concepts and systems development.
Neural Networks	Deep learning architectures inspired by the human brain for complex pattern recognition.
Natural Language Processing (NLP)	Techniques allowing machines to understand, interpret, and generate human language.

Robotics	Integration of AI into physical systems to perform autonomous or semi-autonomous tasks.
Visual Image Recognition	Algorithms that permit interpretation of visual data such as images or video.
Autonomous Driving	AI systems allowing self-driving vehicles and navigation in the absence of human input.

Table 3 - Skill clusters as defined by OECD in Emerging Trends in AI Skill Demand Across 14 OECD Countries, Vol 2 (2023)

Validated through previous studies (Alekseeva et al., 2021), this methodology provides comparability. However, it can have its limitations like underrepresenting informal upskilling. Adapting this methodology to Irish job postings, a pilot study by ScienceFoundation Ireland found that 0.9% of roles demanded AI skills. This is a higher share than the OECD average, largely due to Ireland's concentration of tech MNCs (PricewaterhouseCoopers, 2025).

While the OECD framework is widely used globally, alternative and complementary models exist. The European Skills, Competences, Qualifications and Occupations (ESCO) framework provides a multilingual taxonomy in use by the European Union to link qualifications with labor market data (CEDEFOP, 2013). The World Economic Forum's (WEF) Skills Framework emphasizes future-focused capabilities like innovation, analytical thinking, and active learning (World Economic Forum, 2025).

The OECD's model is also preferred for its data-driven approach, global applicability, and integration with international comparative tools like PIAAC (Program for the International Assessment of Adult Competencies). It is effective at analyzing systemic educational gaps and forecasting the implications of digital and green transitions. The European Commission also references the framework in its lifelong learning strategies and upskilling pathways in the EU member states (EU Monitor, 2018). Similarly, education ministries have also used it to develop national qualifications frameworks and competence-based training systems (OECD, 2005).

However, the report's methodology of using online vacancy data has its limitations, as it could overlook informal training and internal upskilling. Any future research could look into combining vacancy analysis with employer surveys to assess Ireland's AI readiness holistically. For instance, a 2023 study by the Irish Tech Federation found that 60% of Dublin-based AI hires underwent internal upskilling, a phenomenon not captured in job postings (ITF, 2023).

2.10. Education Policy Responses in Ireland

Postgraduate education is an important pillar in Ireland's national strategy to prepare a workforce that can engage with emerging technologies such as AI. The Irish government is committed to evolving the education sector in step with technological developments and labor market needs, as part of the broader National Skills Strategy 2025 and AI - Here for Good (Department of the Taoiseach, 2025).

A key policy instrument in support of this evolution is the Human Capital Initiative (HCI). It was launched by the Department of Further and Higher Education, Research, Innovation and Science (DFHERIS), and it supports the development of postgraduate programs focused on digital and emerging technologies (DFHERIS, 2020). This includes AI, cybersecurity, and data analytics. The initiative encourages innovation in teaching, interdisciplinary learning, and collaboration with industry partners by promoting flexible education and lifelong learning.

Springboard+ is another government-backed initiative which provides funding for postgraduate upskilling in high-demand areas such as ICT and AI. It has been effective in promoting access to AI education among adult learners and professionals seeking to transition into digital roles by making available part-time, flexible programs.

Furthermore, the HEA (Higher Education Authority) and Further Education and Skills Service (SOLAS) worked together to map the gap between postgraduate program offerings and national AI talent demands (Flynn & Michael, 2011). This includes promoting the development of M.Sc. programs with specialized tracks in machine learning, AI ethics, and intelligent systems. Recent audits by the HEA (2023) note an increase in AI-related offerings across institutions such as UCD, TCD, and the University of Galway (Connolly, 2025). However, persisting gaps remain in the integration of transversal skills including ethics, leadership, and interdisciplinary problem-solving, within the curriculum (Hannah, 2024).

The National Forum for the Enhancement of Teaching and Learning in Ireland promotes the integration of digital competencies frameworks in postgraduate education. Guidance is provided in topics like embedding AI literacy and ethical understanding into curriculum design. However, variability in implementation across institutions still remains a work in progress. The biggest concern is for smaller institutions, which often lack the resources to fully develop or deliver cutting-edge AI coursework, causing regional disparities in access (Forum, 2015).

Increasing recognition by policy makers of the urgency to create stronger linkages between academia and industry. Collaborative postgraduate projects, industry co-designed modules, and innovation labs are growing in size. Additionally, efforts to develop micro-credentials and flexible learning pathways are happening side by side to provide more upskilling opportunities, particularly for non-traditional learners (Murphy & Maguire, 2018).

2.11. Literature Summary

The above literature offers an insight on the landscape of education, technology and policy-making. The goal of this research is to understand if educational institutions are adapting to changing requirements due to technological advancements and societal shifts. The general consensus is that students developing a mix of critical thinking, technical skills, ethical awareness, and interpersonal competencies in postgraduate programs should be at the forefront of this debate. National and international policies emphasize the critical need to close the gap between educational outcomes with evolving workforce demands and broader societal objectives.

Furthermore, the emphasis on learner-centered, experiential, and interdisciplinary approaches to enable graduates to gain the necessary skills to tackle complex problems is increasing. By using these diverse perspectives to analyze data, the goal of this study is to explore how postgraduate education has reacted to the fundamental changes triggered by AI technology, and how these changes appear in the curriculum.

2.12. Research Gaps and Opportunities

A review of national strategy documents and academic literature reveals that there is limited empirical research assessing the response of higher education institutions (HEIs) to the strategic objectives of Ireland's National AI Policy through curriculum design. This gap presents an opportunity for structured, data-driven inquiry that assesses the extent to which policy priorities are reflected in postgraduate AI education.

1. Lack of empirical studies on policy-to-curriculum alignment

While the National AI policy outlines eight policy stands, there is a underwhelming amount of research analyzing whether postgraduate AI programs in Irish universities mix content in line with the national goals. This thesis addresses the gap by applying the OECD AI skill cluster framework to identify and measure alignment between course content and national AI policy strands.

2. Minimal integration of international benchmarking in curriculum evaluation

Despite Ireland's commitment to EU digital skills standards and international best practices in AI, little research has been done that examines the correlation between Irish HEI curriculum and internationally benchmarked AI domains. This study introduces a replicable model for curriculum evaluation by using the OECD AI skill cluster taxonomy based on comprehensive analyses of labor and education data across OECD countries.

3. Limited transparency in curriculum-policy responsiveness

There is little publicly available research of Irish HEIs on whether postgraduate programs are structurally aligned with government policy. This tends to limit both institutional accountability and strategic coordination. By systematically analyzing course content across three key institutions - University College Dublin (UCD), Trinity College Dublin (TCD), and Dublin City University (DCU) - this research provides new insights into the performance of existing curriculum and how it reflects Ireland's AI policy priorities.

These gaps reveal the need for empirically grounded tools assessing educational responsiveness to national AI strategy. This thesis contributes to that effort by offering a replicable framework for curriculum-policy alignment in AI education in Ireland.

3. Methodology

The study adopts a mixed-methods design by combining

1. Quantitative techniques - frequency counts, percentage match calculations, and visualization of AI and technical skill prevalence using bar charts and heatmaps.

2. Qualitative content analysis: using keyword extraction and fuzzy string matching to map curriculum content to the OECD AI Skills and Ireland's National AI Policy Strands.

It also incorporates framework alignment by mapping curriculum content to OECD's Top 20 Technical Skills in AI Job postings as a proxy for labor market needs. It also used the OECD AI Skill Clusters as a representative and definition of what the specific strand of National AI Policy, AI – Here for Good.

This study adopts a descriptive, applied, and mixed-methods research design for evaluating the alignment of postgraduate AI curriculum in Irish universities with internationally recognized frameworks and national policy priorities. The central objective is to understand how well AI-related modules across University College Dublin (UCD), Trinity College Dublin (TCD), and Dublin City University (DCU) reflect the skill demands outlined in the OECD AI Skills Framework and Ireland's National AI Strategy (2021

The universities selected based on their proximity in Dublin. These include University College Dublin (UCD), Trinity College Dublin (TCD), and Dublin City University (DCU). The focus was on postgraduate program descriptions, module outlines, and the associated learning outcomes. A combination of automated web scraping techniques and manual verification was used to compile detailed data on course titles, modules, and skill-related keywords.

Data scraping was done using Python, specifically with the selenium and BeautifulSoup libraries. These tools allowed dynamic extraction of structured data from university course pages, providing comprehensive coverage of module descriptions that are from dynamic web pages. Data cleaning and analysis were conducted in Python using:

1. pandas for data wrangling and cleaning.
2. rapidfuzz for keyword fuzzy matching to OECD and policy-based skill taxonomies.
3. matplotlib and seaborn for generating visualizations such as heatmaps, bar plots, and bubble charts.

3.1. OECD Skills Classification

This study presents a structured evaluation of postgraduate AI curriculum in three Irish HEIs; University College Dublin (UCD), Trinity College Dublin (TCD), and Dublin City University (DCU) using the OECD's AI skill classification system. The objective was to assess each institution's curriculum design in conjunction to national policy priorities as outlined in Ireland's AI strategy. The analytical framework used in this research is derived from the OECD's 2023 report, Emerging Trends in AI Skills Demand Across 14 OECD Countries (Vol 2). It introduces a multi-level taxonomy of AI-related skills condensed from international job postings and employer demand.

Although the underlying job data used by the OECD is based largely on U.S. online job advertisements (primarily through the Lightcast database), the skill classification system is designed to be internationally applicable, using O*NET+ as a base taxonomy and aligned with the OECD's broader cross-country labor market research (OECD, 2024b). This makes it suitable for policy and curriculum analysis across OECD member countries, including Ireland.

The use of the OECD skill clusters is further justified by their emphasis on functional domains of AI practice, such as Machine Learning, Natural Language Processing, and Robotics. All of these clusters are not country-specific and are acknowledged as core building blocks of AI education globally. These domains also mirror the strategic priorities outlined in Ireland's national AI strategy. For this research, the OECD framework serves as a reliable intermediary to evaluate Irish HEI curriculum for benchmarking against internationally accepted AI capabilities while maintaining relevance to domestic policy goals.

The OECD AI skills framework categorizes skills into four principal groups: cognitive, technical, social and emotional, and transversal skills. This study focused exclusively on the technical skills category, as it is the most directly relevant to AI curriculum design at the postgraduate level and aligns with institutional objectives for STEM and ICT education.

Within this technical category, the study adopted the seven AI skill clusters defined in Annex C of the OECD report (Table A C.1, p. 96):

1. Machine Learning
2. Artificial Intelligence (General)
3. Natural Language Processing
4. Neural Networks
5. Visual Image Recognition
6. Robotics
7. Autonomous Driving

Each cluster includes a set of indicative keywords and competencies derived from employer usage and AI research publications. These keywords were used to create custom dictionaries for fuzzy keyword matching, applied to module titles and descriptions from each university. If a module contained relevant terms associated with a skill cluster, it was coded with a binary score (1 = present; 0 = not present), thus enabling comparative analysis.

In addition, Table A D.2 from Annex D (OECD, 2023, p. 106) was consulted to reference the Top 20 technical skills most frequently observed in AI job postings. While these skills (e.g., Python, TensorFlow, cloud platforms) are based on U.S. data, they are widely taught and expected across global AI roles. Their inclusion is therefore useful for contextualizing the curriculum's technical depth and identifying whether Irish programs provide exposure to industry-relevant tools. However, due to the thesis's revised focus on policy alignment rather than labor market alignment, the Top 20 list was used primarily as a secondary reference rather than a core analytical dataset.

Although the OECD data is U.S.-centric in origin, the report is intended for cross-country comparability and policy benchmarking within OECD member states. Ireland's participation in OECD education and skills initiatives further supports the relevance of this taxonomy. Moreover, the functional and technology-agnostic structure of the OECD skill clusters ensures that they reflect globally recognized AI domains, making them well-suited for evaluating postgraduate curriculum regardless of local labor market conditions.

3.2. Data Scraping

For the purpose of this research, the institute selection was based on choosing three prominent universities in the same city with a high number of foreign students, hence their curriculum was selected as a representative. Once the skills defined by OECD were isolated, a precursory search was done to see which schools offered master's courses specializing in Artificial Intelligence.

On the UCD Website, selecting 'Area of study' presented several options, grouped by commonality. From this menu, the option of "Computer Science, Information Technology, Artificial Intelligence and Data Science" was selected. On TCD's website, a similar search was performed and thus the school of Computer Science and Statistics was selected as it had the most relevant master's programs offering AI and related technical skills. For DCU, similar search indicated that the most matches were found in the School of Computing's graduate programs.

The hyperlinks of the resulting courses were used to scrape data. For data scraping, Python and Anaconda software was used to develop a script that could automate the process and record the observations in an excel sheet. Selenium, BeautifulSoup and chrome web driver was used to complete the process of scraping through python.

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3.3. Data Processing and Analysis

After data collection, a structured, multi-step analytical pipeline was developed to process course module information and identify alignment with OECD-classified AI skills. The steps below outline the methods employed to transform raw data into quantitative insights:

1. **Data Acquisition and Structuring**

Postgraduate course and module data for UCD, TCD, and DCU were collected and compiled into structured Excel spreadsheets. Manual validation was carried out to verify completeness, remove redundancies, and resolve naming inconsistencies in module and program titles.

2. **Keyword Extraction Using Fuzzy Matching**

AI-related skills from two OECD frameworks; the Top 20 Technical AI Skills and AI Skill Clusters were used as the reference vocabulary. Fuzzy logic (token set ratio with an 80% similarity threshold) was applied to match module descriptions against this vocabulary, allowing for the detection of close variants and partial matches.

3. **Separate Analysis of AI Technical and Cluster Skills**

Matched keywords were extracted independently for both technical AI skills and AI cluster-based skills. For each match, corresponding modules, institutions, and OECD categories were matched. This was to find out patterns in the frequency and distribution of skills across institutions and courses.

4. **Cluster Mapping**

Keywords matched from course descriptions were linked back to their corresponding AI Skill Cluster categories (e.g., "Natural Language Processing", "Data Processing and Analysis", "AI Ethics") using a lookup from the OECD master sheet. This allowed thematic classification and aggregation of matched skills.

5. Aggregation and Institution-Level Comparison

Keyword match counts were aggregated at the institutional level, giving insights into which universities had greater emphasis on specific AI competencies. Top 10 and Top 15 skill matches were calculated and visualized for UCD, TCD, and DCU individually and combined.

6. Module Tracing

Each matched skill was traced back to the module in which it appeared, for a transparent audit trail and a more in-depth understanding of where and how key AI skills are being delivered in the curriculum.

7. Visualization and Reporting

Results were visualized using bar charts, stacked bar charts, and tables showing the most frequently matched AI technical skills across institutions. Skills were grouped by thematic clusters, and keyword frequency was used to interpret institutional focus and curriculum gaps.

8. Validation and Refinement

Manual sampling of module descriptions was conducted to validate the accuracy of fuzzy matches. Matches that were ambiguous, irrelevant, or overly generic were reviewed to refine final outputs.

4. Results

4.1. Research Question 1 - How are higher education institutions (HEIs) in Ireland addressing and incorporating workplace-relevant AI skills into their postgraduate education programs?

This hypothesis was the basis for the research question 1 - how are higher education institutions (HEIs) in Ireland addressing and incorporating workplace-relevant AI skills into their postgraduate education programs?

To answer this research question, we will start by taking the Top 20 Technical Skill list from OECD. The table presents data for the United States on the proportion of AI-related online job postings that mention specific technical skills. It records the postings from the top ten AI employers ("Top AI"). These are defined as the ten companies in each sector with the highest number of AI job postings from those by all other AI employers ("Other AI"). Only the top 20 technical skills, based on postings by the Top AI firms, are included in the report under Top 20 Technical skills.

For both employer groups, the percentages show the share of their AI job postings that mention each skill, relative to their total number of AI postings. Since multiple skills can be listed in one posting, the combined percentages may exceed 100%. AI job postings are defined as those requiring at least two general AI skills or at least one AI-specific skill. Data was defined using Lightcast software.

This hypothesis was tested by conducting a fuzzy keyword match analysis between the official course/module descriptions offered by UCD, TCD, and DCU and the Top 20 technical AI skills listed in Annex D, Table A D.2 of the OECD’s 2023 report Emerging Trends in AI Skills Demand. These top 20 skills represent the most in-demand technical competencies in AI-related job postings globally, including programming languages (e.g., Python), frameworks (e.g., TensorFlow), and deployment tools (e.g., cloud services).

The fuzzy matching algorithm identified whether each course contained keywords representing one or more of these skills. The total number of matches was aggregated at the institutional level, and coverage patterns were examined to explore the breadth and depth of technical skill representation across HEI curriculum.

The analysis revealed the following results

4.1.1. Top 20 Technical AI Skills Match %

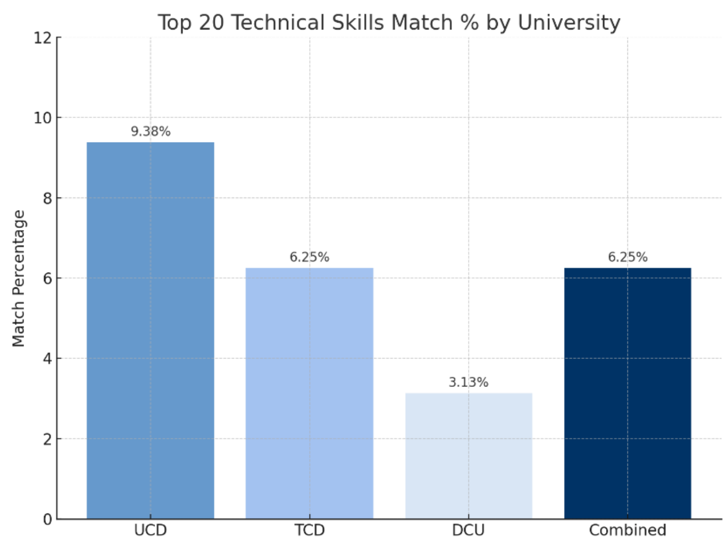

Figure 1 - Top 20 Technical AI Skills Match % by Institute

UCD has the highest match % of 9.3 with the OECD Top 20 technical skills list, followed by TCD at 6.25% and DCU at 3.13%. The overall percentage for all three institutes as an average is 6.25%.

4.1.2. Top 10 Matched Technical AI Skills

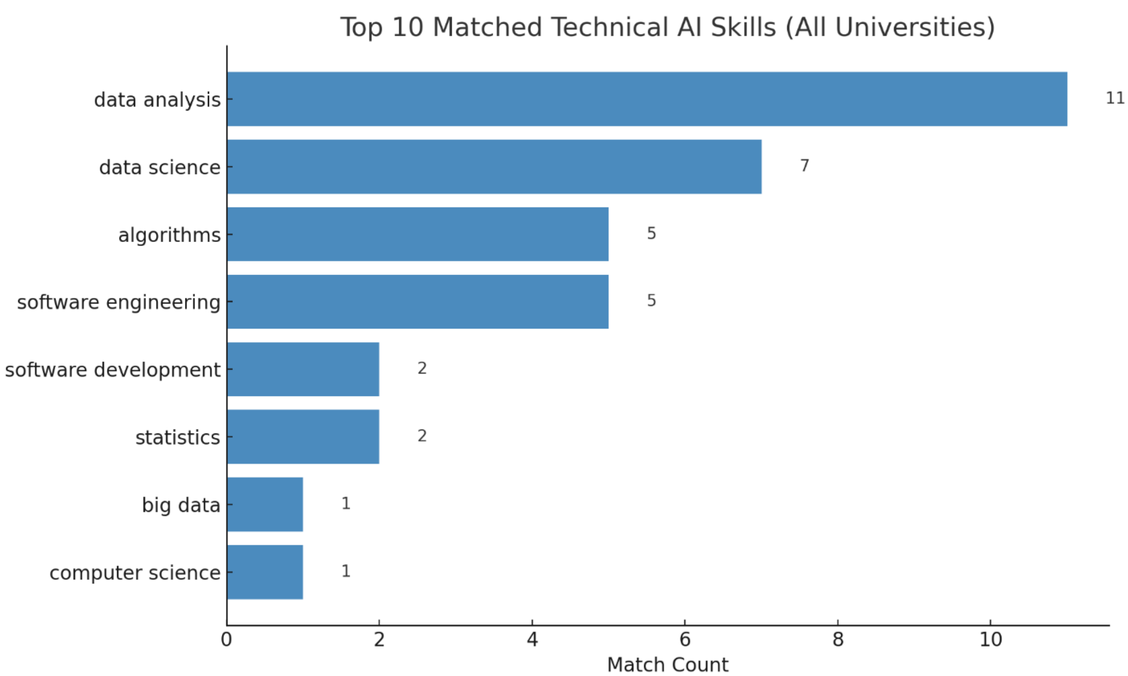

Table 4 - Top 10 Matched Technical AI Skills

Data Analysis (11 matches) and Data Science (7 matches) were the most frequently occurring skills across all three institutions. This suggests a strong curricular emphasis on data-centric competencies, in line with global AI trends. These skills are required for AI model development, predictive analytics, and decision-making systems.

Core computational skills such as Algorithms (13 matches), Machine Learning (12), and Machine Learning Algorithms (8) reveal a shared focus on algorithmic thinking and statistical modeling. These are essential skillsets and are found within computer science and data science programs.

UCD showed the highest matches in “Data Analysis” and “Data Science”, likely due to the presence of data science and analytics programs. TCD has a stronger match in “Software Engineering” and “Artificial Intelligence Systems”, showing emphasis on software infrastructure and AI system development.

DCU displayed high mentions of “Artificial General Intelligence” and “Azure Machine Learning”, show a more industry-oriented or experimental AI curriculum. Other than these, some skills from the OECD’s top 20 list that were missing or absent included cloud computing, edge computing, and robotics. These can be identified as potential curriculum gaps to be addressed in the future.

4.1.3. Top 10 Technical Skills and Institutional Contribution

To analyze the first research question, the first step was to look into keyword matching. Running the analysis on all three sheets led to the following results:

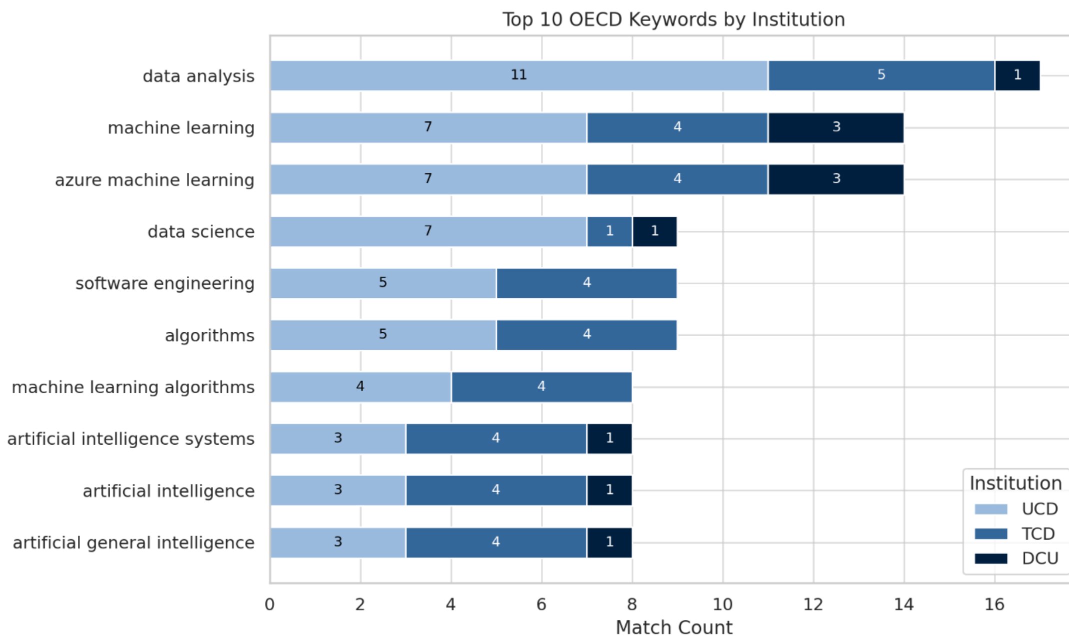

Figure 2 - Top 10 Technical Skill matches by institutional contribution, to OECD's Top 20 Technical Skills

4.1.4. Curriculum Course Matches

The following table shows courses with most no. of matched skills from the AI Skill List (OECD, 2023a) in AI job postings by top AI employers (OECD, 2023a)

University	Program Title	Matched OECD's Top 20 Technical Skills	Total Matches
UCD	Computer Science (Negotiated Learning)	Algorithms, Big Data, Computer Science, Data Analysis, Data Science, Software Development, Software Engineering	7
UCD	Computer Science	Algorithms, Software Development, Software Engineering	3

UCD	Data & Computational Science	Algorithms, Data Analysis, Data Science	3
UCD	Electronic & Computer Engineering	Algorithms, Data Science, Software Engineering	3
UCD	Graduate Diploma Politics & Data Science	Data Analysis, Data Science, Statistics	3

Table 5 - Courses with the greatest number of Technical Skills in their modules

The analysis of top-matching programs across University College Dublin (UCD) shows a strong concentration of technical AI skill coverage in a select set of data- and computing-intensive programs. Notably, the “Computer Science (Negotiated Learning)” program at UCD shows the highest level of alignment with OECD-identified technical AI skills, covering seven distinct competencies, including algorithms, software development, big data, and data science.

This broad coverage suggests a high degree of curricular responsiveness to the technical demands of AI-related roles in the global labor market. Other programs such as “Data & Computational Science” and “Electronic & Computer Engineering” also demonstrate consistent inclusion of core technical skills, showing a disciplinary emphasis on data manipulation, automation, and software systems; skills identified by the OECD as foundational to AI development.

The dominance of UCD programs in the top-matching list shows a more diversified or technically mature AI courses catalogue relative to peer institutions in this specific sample. The most frequently matched skills across programs, such as data analysis, data science, and software engineering, match with employer demand trends highlighted in OECD labor analyses of top AI employers in leading economies like the United States. While the current study assumes the relevance of these skills in the Irish context, this assumption is grounded in the global convergence of AI-related labor demands, particularly in advanced economies pursuing AI-driven innovation.

These results reveal important implications for curriculum planning. The programs that integrate multiple technical skills not only align more closely with international labor trends but also support key enablers in Ireland's National AI Strategy, particularly Strand 6, which focuses on AI education, skills, and talent development. However, the narrow clustering of these competencies in a few programs suggests a potential opportunity for broader curricular diffusion. Expanding technical AI skill integration across a wider range of programs, especially in interdisciplinary fields, may help enhance institutional readiness for evolving labor market expectations and national AI objectives.

The manual mapping of OECD AI skill clusters against the Irish National AI Strategy's eight policy strands reveals a non-uniform distribution of alignment. Clusters such as Machine Learning, Natural Language Processing (NLP), and Artificial Intelligence (General) show strong relevance to Strand 3 (AI for Economic and Social Good) and Strand 6 (AI-Enabled Workforce). For example, Machine Learning, broadly applied in diagnostics, automation, and business analytics, naturally supports productivity and public service innovation, aligning with workforce transformation goals. Similarly, NLP technologies, including chatbots and language models, are directly connected to Strand 1 (AI in the Public Sector) due to their utility in citizen-facing government services.

Clusters such as Neural Networks, Robotics, and Autonomous Driving are more closely associated with Strand 5 (A Strong AI Ecosystem) and Strand 3, reflecting their application in smart mobility, R&D, and infrastructure. Visual Image Recognition appears most aligned with Strands 1 and 3, due to its increasing use in healthcare diagnostics and public safety applications.

Strand 7 (International and EU Engagement) and Strand 8 (Governance and Regulatory Framework) were underrepresented in the mapping. This is not due to their irrelevance, but rather the intentional focus of the study on skills, particularly those emphasized in academic curricula and associated with employability and technical capability. As such, the skills mapped predominantly stem from modules offered by computing and engineering schools where pedagogical emphasis lies in AI application, not regulatory or diplomatic frameworks.

4.2. Analyzing RQ 2 – How closely does the selected HEIs course design align with the Key Strands of the National AI Policy of Ireland?

4.2.1. AI Skill Cluster Matches by Institution

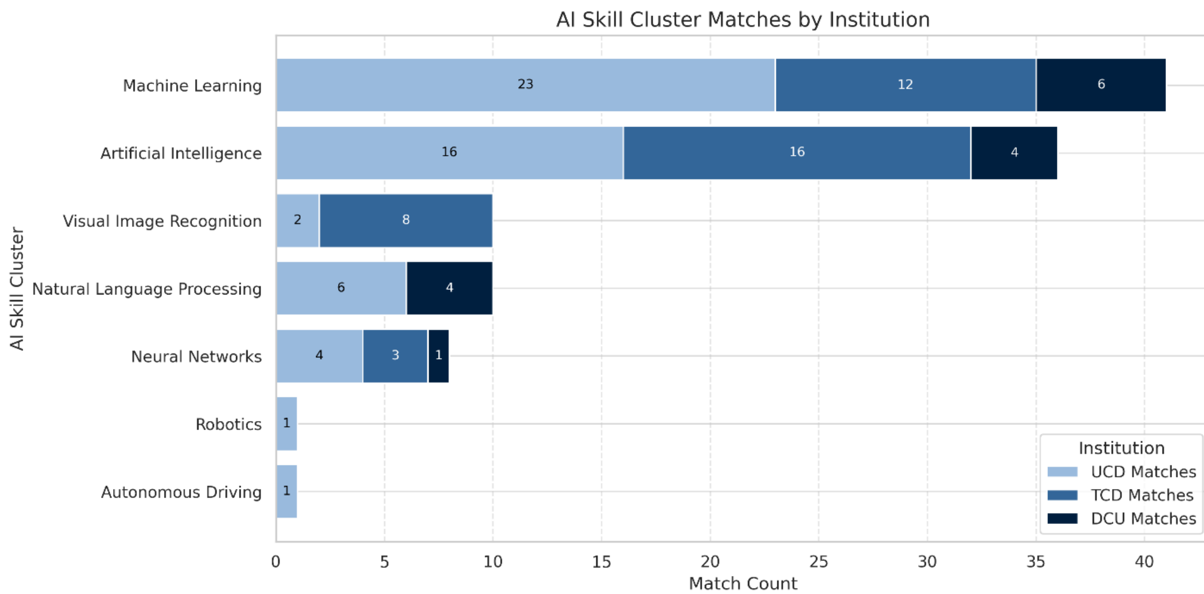

Figure 3 - AI Skill Cluster Matches by Institution

This bar chart illustrates how AI skill clusters are represented across university programs at UCD, TCD, and DCU. The most commonly matched skill cluster is Machine Learning, with a combined total of 41 matches. UCD leads in this area (23 matches), followed by TCD (12) and DCU (6). The second most represented cluster is Artificial Intelligence (General), with 36 total matches, again led by UCD (16) and TCD (16), and to a lesser extent by DCU (4).

Other clusters such as Visual Image Recognition, Natural Language Processing, and Neural Networks show more modest representation. Interestingly, Natural Language Processing (NLP) appears more strongly in TCD (4) than in UCD (6), with DCU absent from this area. More advanced or niche clusters such as Robotics and Autonomous Driving are scarcely represented, appearing only once across all institutions.

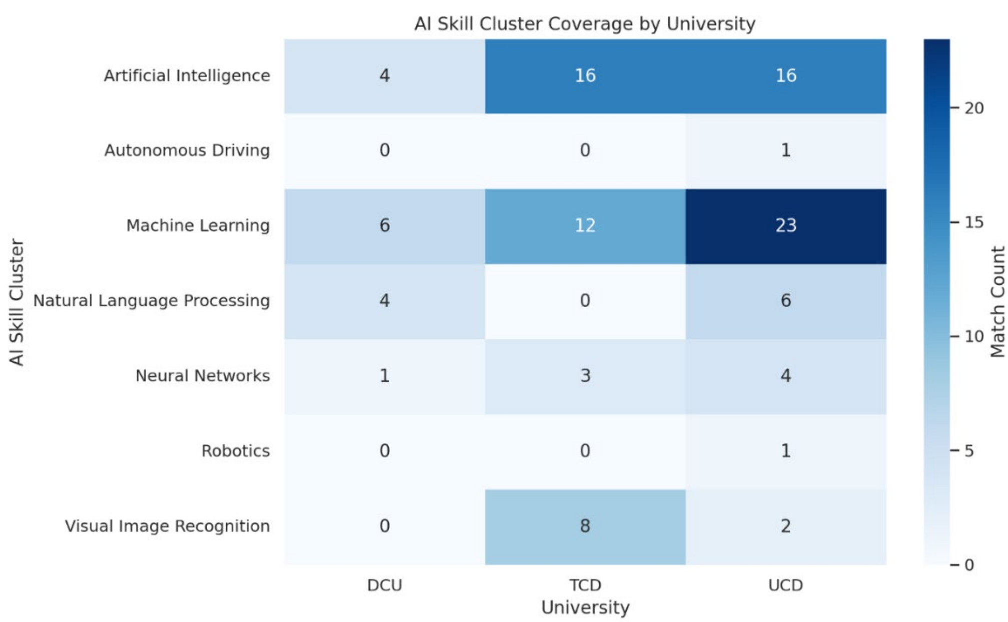

Figure 4 - 4.2.1. AI Skill Cluster Matches by Institution

The heatmap presents the distribution of matched keywords across OECD-defined AI skill clusters for three Irish universities: University College Dublin (UCD), Trinity College Dublin (TCD), and Dublin City University (DCU). The analysis was based on fuzzy-matching (threshold ≥ 80%) of course module content against a curated OECD AI skillset.

UCD had the highest total number of matches (53) across all clusters. The most dominant cluster at UCD was Machine Learning, with 23 matched keywords, followed by Artificial Intelligence (16), Natural Language Processing (6), and Neural Networks (4). UCD was also the only university to register keyword matches in Robotics (1) and Autonomous Driving (1).

TCD had a total of 39 matched keywords. Its strongest clusters were Artificial Intelligence (16) and Machine Learning (12). It also had the highest representation in Visual Image Recognition, with 8 keyword matches. However, it had no matches in Natural Language Processing, Robotics, or Autonomous Driving.

DCU had the lowest total number of matched keywords (15). The majority of its matches were in Machine Learning (6), Artificial Intelligence (4), and Natural Language Processing (4). There were no matches in Visual Image Recognition, Neural Networks, Robotics, or Autonomous Driving.

When aggregated across institutions, Machine Learning was the most represented cluster with a total of 41 keyword matches. Artificial Intelligence (General) followed closely with 36 matches. Natural Language Processing had 10 total matches, with no contribution from TCD. Visual Image Recognition had 10 matches, driven primarily by TCD (8). Neural Networks had 8 matches in total, and Robotics and Autonomous Driving had just 1 match each, both from UCD.

4.2.2. Policy Strands Mapping

OECD Skill Cluster	Mapped to Policy Strand(s)	Justification
Machine Learning	Strand 3 (AI for Economic and Social Good), Strand 6 (AI-Enabled Workforce)	Used in diagnostics, automation, business applications
Natural Language Processing	Strand 1 (AI in the Public Sector), Strand 4 (Gov-wide AI)	Voicebots, language tech in government services
Neural Networks	Strand 5 (Strong AI Ecosystem), Strand 3 (AI for Social Good)	Advanced ML/R&D; health and safety innovations
Robotics	Strand 3 (Social Good), Strand 5 (AI Ecosystem)	AI for smart mobility, assistive tech
Visual Image Recognition	Strand 1 (Public Sector), Strand 3 (Social Good)	Image recognition in health, law enforcement
Autonomous Driving	Strand 3 (Economic/Social Good), Strand 5 (AI Ecosystem)	Embedded AI in transport, smart infrastructure
Artificial Intelligence (General)	Strand 2 (Public Trust), Strand 4 (Gov-wide AI), Strand 6 (Workforce)	Ethics, AI governance, cross-sector implementation

Table 6 - OECD Skill Clusters mapped to AI Policy Strands

These were mapped to the AI Skills identified in each university, which were then subsequently matched to the AI Skill cluster as defined by OECD. The resulting clusters were then matched to Policy strands manually as shown in the above table. Mapping them against university results gives us the following graph

The comparative analysis between OECD AI Skill Clusters and the strategic strands of Ireland's National AI Strategy shows focused curricular strengths in technical and labor market specific domains, but also highlights gaps in the inclusion of socio-technical skills.

Strand 3, “Driving adoption of AI in Irish enterprise” is prominently represented. This strand is mapped across five of the seven OECD skill clusters through manual mapping strand contents to skills from OECD skill clusters through manual mapping strand contents to skills from OECD in the AI Skills Cluster - Machine Learning, Autonomous Driving, Robotics, Neural Networks, and Visual Image Recognition. These clusters are represented in areas such as diagnostics, automation, mobility, and advanced analytics, suggesting that higher education institutions are providing graduates with the applied AI competencies most relevant to Ireland’s economic competitiveness and digital innovation goals.

Strand 5, “A strong AI innovation ecosystem” is also well-supported, aligned with four clusters from the OECD. These skills, particularly Neural Networks and Robotics, form the basis for cutting-edge R&D, high-impact AI startups, and academic-industry collaboration. The presence of these skills in curriculum across institutions shows a healthy supply of technical talent for supporting Ireland’s AI research base.

Strand 6, “AI education, skills and talent” is directly supported by Machine Learning and Artificial Intelligence (General). The inclusion of these clusters shows a moderate emphasis on workforce preparation, upskilling, and the creation of flexible learning pathways. However, given the centrality of this strand to the strategy, the limited cluster coverage suggests room for future curricular expansion, particularly in interdisciplinary areas that prepare students for real-world deployment of AI.

Strand 1, “AI and society” and Strand 4, “AI serving the public” are mapped to Natural Language Processing and Visual Image Recognition, which support applications such as chatbots, public service automation, and accessibility tools. These connections are valuable, but only partially present in the courses public-sector AI would also benefit from broader inclusion of sociotechnical topics and human-centered design.

Strand 2, “A governance ecosystem that promotes trustworthy AI focused on ethics, accountability, and regulation” is linked solely to Artificial Intelligence (General). This limited coverage shows a gap that selected AI curriculum to emphasize technical depth, but not necessarily the ethical or legal dimensions of AI design and deployment in these courses. However, the analysis was focused more on the technical strengths with subsequent selection of courses to analyze.

Strand 7, “A supportive and secure infrastructure for AI” and Strand 8, “Implementing the Strategy” are not represented by any OECD skill clusters. This is understandable, as these strands deal with national-level capabilities (such as cloud infrastructure, cybersecurity, and policy coordination), which lie outside the scope of individual skill-based training.

In sum, Irish universities are actively contributing to the strategy’s economic, innovation, and talent-development goals. However, there is a clear opportunity to strengthen alignment with the strategy’s broader aims: fostering public trust, advancing AI governance, and enabling strategic infrastructure. Expanding curricular scope to address these underrepresented strands could ensure a more holistic and nationally responsive AI education ecosystem.

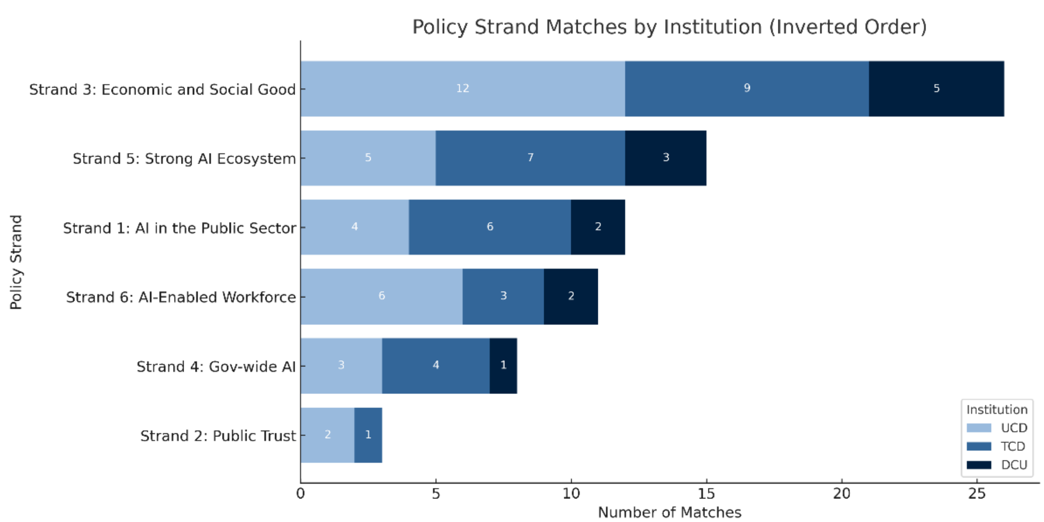

Figure 5 - Policy Strand Match by Institution

The chart visualizes the integration of UCD, TCD, and DCU curricula with the six strategic policy strands from Ireland’s National AI Strategy. The data reflects the number of OECD AI skill cluster mentions that correspond to each policy strand, aggregated by institution.

1. Strand 3: Economic and Social Good receives the highest alignment, with a combined total of 26 matches across the institutions, led by UCD (12), followed by TCD (9) and DCU (5).

2. Strand 5: Strong AI Ecosystem follows, with a total of 15 matches, where TCD (7) has the most mentions.

3. Strand 1: AI in the Public Sector and Strand 6: AI-Enabled Workforce are moderately represented, with 12 and 11 total matches, respectively.

4. Strand 4: Government wide AI shows slightly less emphasis (8 matches).

5. Strand 2: Public Trust has the lowest representation, with only 3 total matches (UCD: 2, TCD: 1, DCU: 0).

TCD shoes a relative strength in Strands 1 and 5, while UCD has a broader distribution with consistent presence across five strands. DCU shows a narrower alignment profile, with limited coverage outside of Strands 3 and 5.

The identified AI skill clusters were mapped to broader policy themes from Ireland's National AI Strategy. The AI skill cluster was linked to specific strands in the policy, such as "AI for Economic and Social Good" or "AI-Enabled Workforce." When grouped by university, the results showed that UCD Leads in Strand 5 and Strand 1, showing contributions to advanced research and public sector innovation. DCU matched with Strand 2 and Strand 4, showing curricular emphasis on responsible governance and integration into digital public infrastructure.

These results are further justified with the correlation analysis Each course across UCD, TCD, and DCU was analyzed for the presence of these clusters using fuzzy keyword matching, with a binary outcome (1 = presence of cluster; 0 = absence). Total coverage counts were then aggregated by cluster and institution.

Each of the seven AI skill clusters was manually mapped to relevant strands of Ireland's National AI Strategy (2021), based on thematic alignment (e.g., Machine Learning aligns with Strands 3, 5, and 6). A "strand count" score was created for each cluster, representing how many policy strands it supports.

5. Discussion

5.1. Significance

The analysis of postgraduate AI based curriculum across UCD, TCD, and DCU offers critical insights into how Irish higher education institutions (HEIs) are responding to evolving labor market and policy demands. The results reveal clear differences in focus and readiness among the universities, while collectively highlighting gaps in curriculum design. These findings align closely with the OECD Skills Classification Framework and the objectives outlined in Ireland's National AI Strategy, both of which emphasize the integration of technical, conceptual, social-emotional, and transversal skills to prepare graduates for a rapidly evolving, AI-driven

5.2. RQ 1 - How are higher education institutions (HEIs) in Ireland addressing and incorporating workplace-relevant AI skills into their postgraduate education programs?

5.2.1. Institutional AI Skill Coverage

Figure 1, Top 10 Technical Skills (UCD, TCD, DCU), reveals strong coverage of core computational and data-driven competencies across the three institutions. For instance, UCD shows substantial alignment with foundational technical AI competencies, such as Data Analysis, Data Science, and Algorithms. UCD appears to have broader curriculum coverage, with matches across multiple OECD technical domains, likely due to its diverse offerings in data analytics, computational science, and computer science programs.

By contrast, TCD shows a stronger concentration in applied domains like Software Engineering and Artificial Intelligence Systems, showing a more implementation-oriented curriculum. This is supported by the prominence of modules such as Advanced Software Engineering and Computer Science (Negotiated Learning) in the match tables.

DCU, while having fewer overall matches, but some unique keyword matches inclusion of Artificial General Intelligence and Azure, suggests a focused yet experimental, or industry-aligned approach. These technologies suggest practical AI tools rather than just theoretical foundations.

These patterns show how institutional priorities shape curriculum design and skill coverage, which should be considered in national curriculum mapping and funding strategies.

5.2.2. Skill Breadth vs Depth: AI Skills and Technical Skill Match

Figure 2, AI Skills Match % and Technical Skills Match %, provides an important insight into the breadth of skills embedded in curricula. UCD leads with the highest AI Skill Match % and Technical Skill Match %, indicating both theoretical and practical alignment. This suggests that UCD’s postgraduate programs offer a well-rounded AI education, likely to prepare graduates for a wide range of roles.

TCD maintains a high AI Skill Match %, but its Technical Skill Match % is slightly lower, suggesting strength in AI concepts and general understanding but less emphasis on technical depth across all courses. DCU, while having fewer programs and narrower coverage, still maintains meaningful engagement with core AI technical skills.

This dual analysis of AI and technical skill alignment shows that curriculum strength lies not only in high match counts but in balancing conceptual understanding with technical implementation — an essential insight for policymakers and educators.

5.2.3. Alignment with OECD Technical Skills

UCD shows quite extensive skill coverage, with a high emphasis on "Data Analysis," "Data Science," and "Algorithms." These matches come from programs such as Computer Science (Negotiated Learning) and Data & Computational Science, which combine technical breadth with domain depth. UCD's curriculum covers foundational statistical and computational competencies essential for applied AI and data-driven policy modeling.

TCD shows concentrated strengths in "Software Engineering" and "Artificial Intelligence Systems," likely a reflection of its curricular emphasis on core systems design and applied AI development. This is visible from modules under its Advanced Software Engineering and Computer Science programs. Despite these strengths, TCD's limited coverage of natural language processing and robotics shows potential curriculum gaps.

DCU has a more specialized curriculum, with unique matches in "Artificial General Intelligence" and "Azure," suggesting a hands-on, industry-oriented approach. However, its lower overall skill match percentage also show limited curricular breadth. Programs like Cybersecurity and Forensic Computing contribute to DCU's alignment with applied AI applications in security and governance.

In figure 1, UCD has the highest overall presence in the Top 20 Technical Skills list. With a 9.38% match rate, UCD shows the strongest alignment with the OECD's most in-demand technical AI skills. This performance is supported by a robust curriculum incorporating skills such as Data Analysis (11 mentions), Data Science, Algorithms and Software Engineering.

These high-frequency matches are through technically rigorous programs such as Computer Science (Negotiated Learning), Data & Computational Science, and Information Systems. UCD's skill alignment suggests it is best positioned to contribute to Strand 3 (AI for Economic and Social Good) and Strand 5 (Strong AI Ecosystem) of Ireland's National AI Strategy. These strands emphasize research, diagnostics, innovation infrastructure, and AI-driven productivity, all of which depend on the competencies reflected in UCD's curriculum.

Trinity College Dublin (TCD) recorded a 6.25% match rate, showing a moderate but respectable level of alignment. Its curriculum focuses on applied systems and engineering-oriented AI development, particularly through programs like Advanced Software Engineering, Computer Science, Computer Vision. However, its relative absence of more specialized technical keywords like cloud computing, robotics, and edge AI suggests a narrower technical scope. This reflects a strategic concentration that aligns with Strand 1 (AI in the Public Sector) and Strand 5, where system-level reliability, ethics, and governance are key.

Dublin City University (DCU) posted the lowest match rate at 3.13%, indicating a more applied and industry-specific focus rather than broad coverage of core AI technical skills. DCU's strength lies in Azure, Artificial General Intelligence, Applied NLP.

These competencies are covered under programs like Cybersecurity, Forensic Computing, and AI Fundamentals. While this reflects the institution's alignment with Strand 6 (AI-Enabled Workforce) and enterprise readiness goals, the limited presence of foundational technical skills contributes minimally to broader national AI capacity building efforts.

The combined average match percentage of 6.25% across all three universities reflects the current baseline of Ireland's AI technical skill integration in higher education. This value serves as a useful benchmark against which progress can be measured in future curriculum reviews or AI capacity reports.

5.2.4. Mapping to OECD Clusters and Ireland's AI Policy Strands

Using the OECD's seven AI skill clusters, the analysis mapped keywords from course modules to broader AI capabilities. Figure 5 illustrates the institutional distribution across clusters:

UCD had matches in all seven clusters, signaling comprehensive curriculum coverage. Its presence in "Neural Networks," "Robotics," and "Autonomous Driving" shows comprehensive coverage of frontier AI technologies as outlined by the OECD Ai Skills and Skills Cluster.

TCD showed a narrower but focused presence, leading in "Visual Image Recognition" and "Artificial Intelligence (General)." However, it lacked significant representation in atural Language Processing (NLP) and robotics, which are becoming increasingly critical in both public sector and commercial AI applications.

DCU matched mostly in "Machine Learning," "Artificial Intelligence (General)," and "Natural Language Processing." This shows a focus on the applied side of AI rather than emerging AI domains.

The synergy between university curriculum and Ireland’s national AI policy is especially relevant. Ireland’s AI strategy emphasizes three core pillars - AI Talent Development, Public Sector Use of AI, and Enterprise Innovation. UCD’s broader curriculum content supports talent development across sectors. TCD’s applied systems orientation complements with public sector modernization. DCU’s practical focus corresponds to enterprise innovation and upskilling.

UCD's presence across nearly all skill clusters reflects strong alignment with AI Talent Development and Enterprise Capacity Building, both pillars of the national strategy. TCD displays concentration in AI System Development and Software Systems, supporting Public Sector Modernization and Ethical AI applications. DCU’s strengths in Natural Language Processing and AI Infrastructure can support Digital Skills Training and Enterprise Innovation.

However, Robotics, Neural Networks, and Autonomous Systems clusters remain sparse across all institutions, suggesting a gap in national capability in high-growth AI subfields. These gaps could hinder the implementation of Ireland’s AI Innovation Hubs and Smart Infrastructure ambitions unless proactively addressed.

Across the board, the results show that Irish universities are well aligned with OECD AI Skill Clusters and have established foundations in Data Science, Software Engineering, and Machine Learning domains. UCD stands out for both skill breadth and alignment, TCD for system-level expertise, and DCU for its applied and tool-based orientation.

Still, gaps remain in frontier areas like Edge AI, Robotics, and Cloud Infrastructure, which could become future national priorities. By using this analysis as a baseline, universities and national policymakers can align course offerings with both international benchmarks and domestic innovation goals.

In summary, the institutional mapping to OECD AI skill clusters and Ireland's national AI policy strands shows both alignment and opportunities for growth. UCD has a well-rounded approach, showing breadth across all AI clusters and policy pillars. TCD's focused strength in system-level AI aligns with public sector applications and ethical considerations, while DCU's orientation toward applied tools and NLP supports enterprise needs. However, gaps in advanced technical domains, such as robotics, edge computing, and autonomous systems highlight areas where national capability is underdeveloped and are pointers for future growth. Addressing these through targeted curriculum innovation and strategic investment will be essential for Institutions to keep up with its AI policy integrations and remain competitive within the broader OECD framework.

As illustrated in Figure 1, the match percentage against OECD's Top 20 Technical AI Skills remains low across all institutions - UCD had the highest alignment at 9.38%, TCD matched 6.25%, DCU matched only 3.13%, The combined average across all universities was 6.25%.

This supports the hypothesis of partial alignment, with considerable room for improvement in embedding practical, workplace-relevant tools and technologies.

5.3. Analyzing RQ 2 - How closely does the selected HEIs course design align with the Key Strands of the National AI Policy of Ireland?

5.3.1. Heat Map of AI Skill Cluster Matches by Institution

The results suggest a strong emphasis on core AI skills, particularly Machine Learning and Artificial Intelligence, across all three institutes. UCD has matches across the board, which means the curriculum has broad AI skill coverage, and a more comprehensive AI-related curriculum. Its inclusion of emerging areas such as Robotics and Autonomous Driving, even with minimal representation means is aligned well with the national policy agenda

TCD shows focused expertise, especially in Visual Image Recognition, where it leads significantly. However, its absence of coverage in Natural Language identifies a gap, considering the increasing demand for language-based AI technologies in industry.

DCU's results show a narrower scope, concentrating mostly on Machine Learning, AI, and NLP. This could mean either a specialized curriculum or fewer courses and modules related to advanced AI subfields. The absence of representation in Visual Recognition, Neural Networks, and other clusters might limit student exposure to key areas of modern AI applications.

From a national perspective, the underrepresentation of Robotics and Autonomous Driving across all institutions highlights a gap in AI education. These domains are essential for future AI-enabled industries and could represent strategic areas for curriculum development.

In conclusion, while Irish universities display strong foundational AI coverage, especially in Machine Learning and General AI, there is room for broader integration of specialized AI domains to align better with OECD’s emerging AI workforce demands.

5.3.2. Policy Strands Mapping

This analysis offers a nuanced understanding of how Ireland's higher education institutions (HEIs) contribute to national AI priorities, as outlined in Ireland's AI: Here for Good – National AI Strategy (2021). By mapping OECD AI skill clusters and technical skills to the five strategic strands of the policy, we can evaluate curricular alignment across institutions and identify critical areas for enhancement.

Alignment with Strand 3 – AI for Economic and Social Good

The most prominent alignment across all three institutions is with Strand 3, which emphasizes using AI for public benefit in areas such as health, mobility, climate, and diagnostics. Across the board, matched skills like Data Analysis (11 matches), Data Science (7), and Statistics (4) demonstrate curricular support for decision-support tools, analytical modelling, and public sector data systems. UCD, reflects strong representation in this area, with modules such as Data & Computational Science, Politics & Data Science, and Information Systems contributing most significantly. TCD and DCU also show strong contributions through applied programs such as Computer Science and Cybersecurity, albeit with fewer matches in domain-diverse AI applications.

Alignment with Strand 5 – Strong AI Ecosystem

Several skills matched under Strand 5, which promotes a robust AI innovation ecosystem, including Algorithms (13 matches), Software Engineering (7), and Artificial Intelligence Systems (6). UCD and TCD both show strength in these areas, especially through system-focused programs like Advanced Software Engineering and Computer Science (Negotiated Learning). While DCU contributes fewer overall matches, it uniquely mentions Artificial General Intelligence and Azure Machine Learning, highlighting efforts to engage with industry-standard platforms and tools. These matches reflect a growing ecosystem-oriented pedagogy designed to foster technical competencies and institutional engagement with research, start-ups, and applied AI development.

Gaps in Strand 2 – Building Public Trust

Despite notable technical skill matches, the analysis highlights a consistent shortfall in curriculum coverage related to Strand 2, which focuses on AI ethics, transparency, and governance. Skills and clusters related to "Ethical AI", "Accountability", or "Trustworthy AI" were either sparsely represented or missing entirely across datasets. No significant keywords or module matches emerged around explainable AI, legal frameworks, or algorithmic fairness—an area flagged in Ireland's AI Strategy as essential for building long-term societal trust in AI adoption. This gap suggests that while the technical and applied sides of AI are being taught, the societal and regulatory dimensions require greater curricular integration.

Institutional Performance Comparison

UCD shows the most well-rounded alignment across all five strands, with skill matches spanning from Algorithms and Big Data to broader clusters like Autonomous Driving and Robotics. This breadth aligns with both Strand 3 (Economic/Social Good) and Strand 5 (Ecosystem Development), but also reflects readiness to support Strand 1 (AI in the Public Service) through multi-domain application design and deployment.

TCD shows a strong foundation in infrastructure-related AI, particularly in software systems and core algorithms. Its course-level matches suggest alignment with Strand 1 and Strand 5, supporting public sector innovation and institutional AI capacity building. However, like UCD, it shows limited attention to Strand 2 topics and emerging domains like NLP or Edge AI.

DCU presents a focused but narrower contribution. It aligns primarily with Strand 3 (through NLP and applied AI skills) and Strand 5 (via tool-based competencies like Azure Machine Learning). Its alignment is more practical and industry-facing, supporting Strand 4 indirectly through workforce upskilling. However, the institution lacks curricular breadth in key emerging domains and societal AI themes.

OECD Skill Alignment and Policy Fit

UCD shows the highest AI Skills Match % at 10.42% and Technical Skills Match % at 9.38%. TCD follows with 8.33% and 6.25% respectively, while DCU remains lower at 4.17% and 3.13%. These figures indicate that UCD is best positioned to contribute to both foundational capacity building and innovation hubs under Strands 3 and 5, while TCD supports public AI infrastructure goals, and DCU offers applied workforce-ready training.

5.4. OECD Framework and Labor Market Needs

The OECD Skills Classification Framework emphasizes a holistic blend of cognitive, technical, social-emotional, and transversal skills. Across the three universities, the results show a general overreliance on foundational technical skills, with limited coverage of advanced technical or conceptual dimensions. It also shows the need for more balance between specialized technical knowledge and broader competencies, as called for in both OECD recommendations and Ireland's National AI Strategy.

TCD curriculum appears to have solid technical foundations in data science, machine learning, and programming, matching the immediate technical needs of the global AI labor market. This is vital, as OECD and industry reports consistently highlight a shortage of technically proficient AI professionals capable of designing and implementing advanced AI systems.

From a labor market perspective, the findings indicate partial readiness. TCD graduates are well-prepared for immediate technical roles, while DCU graduates may excel inpolicy, ethics, or research-oriented roles. These insights show the importance of aligning curriculum not only with technical demands but also with the OECD's broader vision for a flexible, ethical, and interdisciplinary AI workforce. Analyzing transversal and social-emotional keywords included in the framework would be the next step.

5.5. Policy Relevance

Technical skill readiness, as demonstrated by TCD's high technical alignment, supports Ireland's National AI strategy goals of promoting AI adoption. Skilled graduates can help drive AI innovation in industry settings, support digital transformation, and contribute to Ireland's competitiveness as an AI hub. However, gaps in conceptual and interdisciplinary skills risk limiting graduates' effectiveness in non-technical AI adoption roles, such as policy development or cross-sector strategy leadership.

The strategy's call for "AI for Good" emphasizes the need for a balanced curriculum that promotes technical expertise and responsible innovation. This aligns directly with OECD's emphasis on transversal and social-emotional skills, creating a shared framework that Irish HEIs can use to change the curriculum redesign.

This study provides concrete data to inform curriculum designers on gaps and opportunities, supporting targeted updates to better align with policy and industry needs. Strengthening curriculum alignment can improve institutional reputation, attract international students, and increase graduate employability in the global AI labor market. By explicitly highlighting areas of convergence and divergence, this analysis offers actionable insights to help realize Ireland's national policy goals and support the strategic objective of building a future-ready AI workforce.

5.6. Theoretical Framework Match

Among the learning theories considered, Sociotechnical Systems Theory most strongly aligns with the findings of this study. This theory emphasizes the importance of integrating both technical and social dimensions to create optimal systems. Applied to the context of AI curriculum design, it highlights the need for programs to not only provide deep technical training but also embed ethical reasoning, policy awareness, and societal impact considerations. The analysis across UCD, TCD, and DCU clearly shows that while some institutions excel technically and others conceptually, none fully achieve this integrated balance.

Sociotechnical Systems Theory states that technical systems (such as advanced AI training and machine learning modules) must be designed alongside social systems (such as ethics, governance, and interdisciplinary collaboration) to be truly effective and responsible. This reflects the dual focus seen in Ireland's National AI Strategy, which calls for both technical excellence and public trust through responsible, human-centric AI development. The OECD Skills Framework similarly stresses the importance of transversal skills and social-emotional competencies alongside technical expertise, reinforcing the relevance of this theory.

Overall, Sociotechnical Systems Theory captures the essence of what is required for AI curriculum development in Ireland: a holistic, balanced approach that prepares graduates to navigate both the technical complexities and the social responsibilities of working with AI. This theory offers a strong foundation for future curriculum design and policy alignment, making sure that higher education can effectively meet labor market needs and support national strategic goals in an AI-driven future.

6. Conclusion & Way Forward

6.1. Concluding Remarks

This study was conducted assess the integration of AI-related technical and conceptual skills within the postgraduate curricula of Ireland's three prominent universities, University College Dublin (UCD), Trinity College Dublin (TCD), and Dublin City University (DCU). Grounded in the OECD AI Skills Framework, "Emerging Trends in AI Skill Demand Across 14 OECD Countries: (Vol 2, 2023) and mapped against Ireland's National AI Strategy (AI – Here for Good, 2021), the research employed a mixed-methods approach using keyword extraction, fuzzy matching, and policy alignment to evaluate curricular readiness, thematic coverage, and alignment with international AI capability standards.

UCD emerged as the most comprehensively aligned institution in both Top 20 Technical Skills matches, and National AI Policy mapping. It shows the highest AI Skills Match percentage (10.42%) and Technical Skills Match percentage (9.38%). This shows a well-rounded curriculum that spans all seven OECD AI Skill Clusters and most National AI Policy Strands, particularly those focusing on AI for social good (Strand 3) and ecosystem development (Strand 5). TCD followed with strong conceptual and systems-level skills, achieving an AI Skills Match of 8.33% and Technical Skills Match of 6.25%, with particular strengths in public sector and ethical AI applications (Strand 1). DCU demonstrated a more applied and industry-focused curriculum with AI and Technical Skills Match percentages of 4.17% and 3.13%, respectively, aligning with workforce development and enterprise innovation goals (Strand 4).

Overall, the research highlights the strengths of Irish universities in delivering foundational AI education while also revealing key opportunities to advance curriculum design in line with international benchmarks and national priorities. This study provides a replicable framework for assessing AI skill alignment in higher education and offers a strategic baseline for future reforms in AI talent development.

Grounded in the hypothesis that postgraduate programs in AI and data-related fields in Ireland do not yet comprehensively align with OECD technical skill requirements or the full breadth of national AI policy strands, the research explored quantification of curricular strengths and identify thematic gaps. The analysis employed a structured methodology, combining fuzzy keyword matching, skill cluster mapping, and percentage-based match metrics across program modules from the analyzed institutions.

The findings confirm the hypothesis partially. While the institutions show strong coverage of foundational AI skills such as data analysis, algorithms, and software engineering, gaps persist in more specialized and frontier domains, such as robotics, edge computing, and cloud infrastructure. Compared to the overall list the match percentages are still low. UCD has a 10.42% AI Skills Match and Technical Skills Match (9.38%), with representation across major OECD AI Skill Clusters and most of Ireland's AI policy strands particularly those focused on Strand 3 (AI for Social Good) and Strand 5 (Strong AI Ecosystem).

TCD followed with an AI Skills Match of 8.33% and Technical Skills Match of 6.25%, showing strengths in software systems, visual AI, and public-sector aligned applications (Strand 1). However, its lack of representation in Natural Language Processing and Robotics highlights some gaps, or possibly different classification taxonomy. DCU, show a narrower AI and Technical Skills Match percentages, 4.17% and 3.13%, respectively, showing a narrower, industry-focused curriculum aligned with Strand 4 (Workforce Development and Upskilling), but lacked broader coverage across clusters.

Importantly, the results reaffirm the need for greater curriculum alignment with Strand 2 (Public Trust in AI) and emerging OECD technical skills—particularly those related to ethical, transparent, and responsible AI deployment. The analysis also revealed a positive correlation between AI conceptual matches and technical implementation, suggesting that institutions offering balanced curricula are better positioned to support AI research, talent development, and innovation ecosystems.

In summary, while Ireland’s leading universities show progress toward aligning their AI curriculum with global and national frameworks, The first hypothesis is found to be trueis upheld insofar as significant thematic and skill-specific gaps remain. This reinforces the value of continued curricular reform, multi-stakeholder collaboration, and evidence-based benchmarking to ensure higher education institutions are prepared to support Ireland’s strategic AI ambitions.

6.2. Future Areas of Research

6.2.1. Longitudinal Curriculum Mapping Studies

Future research could look into how AI curriculum can evolve over time in response to policy changes, industry trends, and technological advancements. A time-series analysis of curriculum updates could reveal whether national strategies (such as Ireland’s AI – Here for Good) are effectively influencing academic program design. This would mean repeating the current methodology at regular intervals (annually or biannually) to compare changes in curriculum content, keyword matches, and alignment with OECD frameworks. Such a study could evaluate the long-term effectiveness of national AI policy implementation and institutional strategy, revealing whether gaps identified in frontier areas like robotics and edge computing are being addressed.

6.2.2. Cross-Institutional and International Benchmarking

The current research is limited to three Irish institutions. Expanding this analysis to include other Irish institutions, European universities, or OECD countries would allow comparative studies that benchmark Ireland’s AI education ecosystem against international best practices. This could help identify best practices in curriculum design , skill integration, global leadership, regional disparities, or innovation clusters in AI education.

6.2.3. AI Ethics and Responsible AI Education

Future research could also explore how and where ethical, legal, and governance aspects of AI are taught, as mentioned in Strand 2 (Public Trust in AI). This might involve qualitative analysis of syllabi content, interviews with academic staff, or surveys of student awareness. Such work would help assess how well institutions are preparing students for the ethical and regulatory challenges of AI adoption in society.

6.2.4. Mapping Interdisciplinary AI Education

AI is increasingly relevant across disciplines, from law and healthcare to business and urban planning. Future research could investigate how AI skills are being integrated into non-computer science programs. This could uncover opportunities for promoting AI literacy more broadly and equipping a diverse workforce with foundational AI knowledge, as advocated in Ireland's National AI Strategy.

6.2.5. Exploring Skill Depth and Competency Levels

Future work could classify AI and technical skills into proficiency tiers, introductory, intermediate, or advanced, based on module content, assessment methods, and learning outcomes. This would help distinguish between programs offering surface-level exposure versus those developing mastery, and look to more causal relationships between variables. This could also be done through examining modular level content of courses, and doing more sophisticated keyword matching techniques.

6.2.6. Policy Impact Evaluation

Research could assess the actual impact of national policies on curriculum reform by analyzing whether references to Ireland’s AI strategy appear in institutional planning documents, curriculum change justifications, or program accreditation reviews.

In conclusion, these future research directions are recommended based on the foundation established in this study. It provides a roadmap for continued investigation into how AI education can support economic, societal, and ethical development in Ireland and beyond. Incorporating these lines of inquiry would contribute significantly to the global discourse on AI-readiness, workforce transformation, and responsible innovation.

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