From Data Literacy to Data Mastery: Enhanced Data-Driven Decision Making (DDDM) In The Age Of AI

A report by Andrew Pope, Simon Woodworth, Huanhuan Xiong of Cork University Business School. Commissioned by the N-TUTORR National Digital Leadership Network

National Digital Leadership Network

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Abstract

Data-driven decision-making is transforming industries like education, healthcare, and finance by harnessing big data and AI. This report explores the critical shift from traditional decision support to AI-powered automation and highlights how these changes impact organisations and society. The report discusses the technology and skills that are currently driving the digital economy and also attempts to reveal what comes next. The report shows examples of best practice across multiple sectors. It also explores "next practice" - future innovations such as edge-cloud computing and responsible AI. These are mapped against the United Nations sustainable development goals (SDGs). With a focus on ethical and sustainable data use, the report offers strategic recommendations for higher education institutions to prepare future leaders. Flexible curricula and a strong data culture are essential for driving innovation while addressing skills needs and ethical challenges in an increasingly data-centric world.

Introduction to the National Digital Leadership Network Report Series

The National Digital Leadership Network (NDLN) is a collaborative initiative designed to support digital transformation across Ireland's Technological Higher Education sector. Established under the N-TUTORR programme with funding provided through the EU's NextGenerationEU initiative, the network was officially launched in November 2024 to provide a national platform for digital leadership and complementary knowledge exchange and strategic collaboration. While the N-TUTORR programme has now concluded, our network continues its work under the guidance of a steering board composed of sector leaders and external experts.

Digital leadership in higher education extends far beyond technical expertise or the adoption of certain tools and platforms: it's about vision, strategy, and culture change. Effective digital leaders ensure that digital strategies and developments align with institutional and national priorities, not only enhancing teaching, learning, research, and administration functions but also upholding academic values, promoting equity, and driving business innovation. In this context, the NDLN fosters collaboration among higher education leaders, policymakers, and practitioners, providing opportunities to share insights, explore emerging challenges, and develop shared solutions.

As part of its work, the NDLN has commissioned a series of horizon-scanning reports authored by leading national and international scholars and practitioners. These reports explore key trends at the intersection of digital innovation, traditional leadership and strategic planning, providing actionable insights to support higher education institutions in aligning these trends and related opportunities with institutional and national priorities. Covering topics such as the evolving role of generative AI in academia, data-driven decision-making, academic integrity, new models of learning and teaching and new ways to plan for financial sustainability, this report series offers timely advice and direction for higher education leaders navigating the interrelated complexities of the digital and post-digital age.

We extend our gratitude to the N-TUTORR programme for its financial support, and to N-TUTORR Co-ordinator Dr Sharon Flynn for her direction and continued support of the network. Thank you also to members of our national steering board and to our external contributors, in particular Professor Lawrie Phipps.

A big personal thank you in addition to my colleagues in the Department of Technology Enhanced Learning (TEL) at MTU -- especially Darragh Coakley and Marta

Guerra -- whose work has been vital to the preparation and publication of these reports. We are also very grateful to Dr. Catherine Cronin, our chief editor, and, of course, to all our authors whose insights, expertise, and dedication form the heart and foundation of this series.

We invite you to engage with these reports and join us in shaping the future of digital leadership in higher education.

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Executive Summary

The unprecedented pace of technological change, best exemplified by products such as OpenAI's ChatGPT, has led to employers and educators scrambling to identify and articulate society's future skills needs. Artificial intelligence (AI), and the big data that feeds it, will change many job descriptions, eliminate some jobs completely, and even create new previously unimagined careers. Conversational AI interfaces, such as ChatGPT, have to some degree democratised data science, meaning that it can be applied across all sectors of the economy.

Though we think of big data and AI as technical subjects, the impact of these technologies is decidedly human. If we take an overly technology-focused approach to skills planning, we run the risk of prioritising short-term gains at the expense of shaping our data-driven, AI-assisted future. In line with Irish and EU policy, the authors of this report advocate data and AI literacy for all students, irrespective of discipline. However, this report goes further by advocating data mastery.

This report introduces the data mastery matrix, which categorises data mastery across two dimensions: skills type (hard and soft) and organisational level (strategic, tactical, and operational). This approach recognises the decreasing durability of high-tech skills, while also facilitating a pipeline of talent that can contribute to the operational, tactical, and strategic objectives of employers. Our higher education sector must play a crucial leadership role in this regard, by producing graduates who can understand the wider implications of adoption of technology and also understand how disruptive technologies can be used to empower rather than replace humans in the workplace. Data mastery is not just about skills, however; it also recognises the important role that our graduates will need to play in addressing ethical and sustainability challenges introduced by new technology.

This report outlines how data mastery is impacted by, and shapes, the United Nations Sustainable Development Goals (SDGs). It proposes a Data Mastery Roadmap, which provides a list of actions, or critical success factors, that will be required to create an environment conducive to helping students attain data mastery. These include universal data and AI literacy; use of the data mastery skills matrix; policy labs; industry and community engagement; and interdisciplinary and inter-institutional collaboration.

Introduction

Though the discourse around big data, data analytics, and generative artificial intelligence inevitably revolves around technology, this reveals only part of the picture. Indeed, a solely technology-focused lens is insufficient to understand the widespread ramifications of this technology. Moving beyond purely technological considerations, this report explores the historical precedents and economic drivers that have catalysed the rise of big data and data-driven decision-making. In doing so, the report illustrates fundamental shifts in how individuals, organisations, and society at large engage with data. Moreover, this report provides a strategic blueprint for educators and institutional decision-makers. The blueprint can help policymakers to anticipate future skills needs, while also building an ethical and responsible data culture that supports research and innovation. This approach provides practical guidelines to facilitate the education journey from data literacy to data mastery.

Through an examination of the higher education sector, but also key sectors including finance, healthcare, manufacturing, and information technology, the report reveals the transformative impact of data-driven decision-making. It reviews national and international initiatives to provide an overview of exemplars in these sectors while also presenting a forward-looking perspective on what happens next. For example, how might edge-cloud computing, with its benefit of low power consumption, contribute to addressing sustainability and energy efficiency challenges? How might the ubiquitous availability of detailed patient data reduce healthcare costs, improve patient outcomes, and drive health policy in Ireland, Europe, and low- to middle-income countries? How can higher education provide the human capital to drive such initiatives?

Our economy is being driven in part by connectivity, data, computational power, analytics, and intelligence, all of which will require both data literacy and additional specialised technical skills. According to the World Economic Forum Strategic Intelligence series on data science, education institutions and educators across all levels have struggled to identify how best to train the workforce of the future (World Economic Forum, 2024). Furthermore, an overly restrictive focus on data science alone may overlook the opportunity to promote basic data literacy among education leaders, policymakers, and the general public. This report will provide clear recommendations for achieving this, including the design of flexible curricula that can be quickly adapted to harness emerging trends and technologies.

Institutions that do not recognise the centrality of data literacy skills risk falling behind in a world where data-driven decision-making fuels competitiveness and innovation, and thus shapes our very society. A recent edX and Workplace Intelligence study, incorporating 800 senior executives and 800 non-executive knowledge workers, found that almost half of executives believed that their workforce was unprepared for the future of work (edX, 2023). Nonetheless, a recent Forrester study commissioned by the analytics software company Tableau revealed that 82% of decision-makers expected at least basic data literacy from all employees, irrespective of their department (Forrester, 2022). Clearly, higher education institutions, and particularly technological universities, must play a crucial role in shaping our data-driven future.

> data-driven decision-making fuels competitiveness and innovation...

Despite the many opportunities and advantages that arise from new technologies, we must also reflect on their potential negative impact. Technologies that create, store, and distribute data on a massive scale introduce ethical, data privacy, and security concerns. There is evidence that some automated and semi-automated decision-making systems are subject to unwanted biases. For example, research shows that women in the workplace will be disproportionately impacted by AI job displacement (McNeilly & Smith, 2023). Moreover, we may witness a new digital divide between those who can afford to pay for access to the latest large language models and those who cannot.

A growing digital economy requires a workforce with skilled engineers, infrastructure specialists, and information technologists. In order to sustain this, it will be imperative that the workforce have digital literacy skills. However, thoughtful leaders are also needed to shape which direction we travel in and consider the wider societal impact of new technologies. This is a view supported by the Expert Working Group on Future Skills Needs in their preliminary report on AI Skills (Expert Group on Future Skills Needs, 2022) and reflects proposals set out by the European Commission (Alcidi, 2024) and the OECD.

Two months after its launch in November 2022, ChatGPT had accumulated over 100 million users, making it the fastest growing consumer application ever (Leslie & Perini, 2024). Despite Ireland launching its National AI Strategy in 2021 (Department of Enterprise, Trade and Employment, 2021), the transformative and disruptive nature of AI technologies – exemplified by the introduction of ChatGPT – necessitated a strategy refresh in 2024 (Department of Enterprise, Trade and Employment, 2024). The adoption of AI is already influencing skills demands and will inevitably lead to a reduction of routine tasks, and indeed the elimination of some roles entirely. Higher education institutions must work closely with businesses to provide guidance on data analytics and AI adoption while simultaneously strengthening links with public research institutes. There is a demand for highly skilled workers to grow the data economy; digital literacy will help them sustain it, but they will need digital mastery to shape it.

This report discusses the impact of big data and AI on the global economy and workforce needs. The report also examines best practice in data science education. Following this, we introduce the concept of data mastery, which is represented using a data mastery matrix framework. Finally, we describe how leaders in higher education can facilitate data mastery by encouraging the use of hard and soft skills across all organisational levels, and we include actionable recommendations for higher education institutions to put into practice. These recommendations are aligned with national strategic priorities and position higher education institutions to lead in a data-driven future.

The Impact of Big Data and AI on The Global Economy and Workforce

In an increasingly digitalised world, the exponential growth of data has led to big data and AI becoming pivotal technologies. Vast amounts of data are generated every second from sources like transactions, enterprise systems, social media, connected sensors, and communications. Such data is often unstructured and incomplete. This “big data” with its large volumes, high velocity, and variety cannot be analysed using traditional approaches. Indeed, transforming this vast, fast-moving data into actionable insights requires specialist skills, which are collectively referred to as data analytics. These large datasets, characteristic of big data, also represent an important source of data for training modern AI models and algorithms. As such, data analytics and AI are interrelated fields that have the potential, when combined, to transform industries by improving decision-making, optimising operations, and unlocking innovation. These technologies have the power to transform both what we do and how we do it.

Though earlier generations of decision-support technologies put the human decision-maker front and centre, the role of the human decision-maker continues to evolve. Modern AI has the potential for truly autonomous decision-making, even though it currently has limitations when it comes to tactical decision-making (Kar & Kushwaha, 2023). Clearly, this will have an impact on current and future skills needs. Policymakers and organisational leaders must consider the strategic impact and policy implication of disruptive technologies. To illustrate this point, consider the tax incentives for capital investment which were offered by the UK government to promote growth and infrastructure. The scheme had the desired effect of increasing IT capital investment. However, cloud computing is not a capital expenditure and was thus excluded from the scheme. As a result, the UK economy experienced slower adoption of big data and AI, as well as a decreased demand for workers with data analytics skills (DeStefano et al., 2024). A policy intended to invigorate the economy ultimately hampered the adoption of data analytics and AI.

Moreover, some earlier definitions of data skills and roles have become outdated when considering the recent and dramatic changes in technology, and the fact that many employees’ roles have changed as a result of big data and AI (Gummer & Mandinach, 2015; Tamayo et al., 2023). Though the academic discourse on the technical aspects (see section on “Technical proficiency (hard skills)”) of data analytics and AI is rich, there remains a gap with regard to the human component (Wolff et al., 2016). Issues such as algorithmic bias and ethics have been widely discussed in the academic literature at theoretical level, but there have been few studies backed by empirical evidence (Kordzadeh & Ghasemaghaei, 2022). Furthermore, principles-based approaches to ethical AI can lack practicality (Bleher & Braun, 2023). Our digital workforce will need to understand as well as apply the latest ethical frameworks, parse policy documents, and adhere to relevant data protection and privacy regulations (see section on "Foundational competencies (soft skills)").

Privacy-by-Design (Cavoukian, 2009) and Ethics-by-Design (Nussbaumer et al., 2023) are practical approaches to embedding ethics and data privacy into the software development process (see section describing 'A data mastery matrix approach'). Teaching students these practical approaches will ensure that ethics and privacy are an integral part of software development, not an afterthought. In addition to applying best practice, we must also provide students with opportunities to take an active role in shaping policy and ethical practices. The introduction of innovative mechanisms such as policy labs (see section on "Policy labs and regulatory sandboxes") will also ensure our students can both contribute to the discourse and shape policy.

Big Data's Transformation of Industries

The introduction of mainframe computing in the 1950s allowed organisations to create and accumulate data on a previously unimaginable scale. Unlocking the potential of this data required new skills that incorporated the fields of computer science and statistics. The resulting discipline of data science, which emerged in the 1960s, helped organisations to make predictions, spot trends, and aid in decision-making. In the intervening years, the means through which we create and store data has changed dramatically. Technology has become increasingly integrated in not only business and education environments but our daily lives as well (see section on "Industry and community engagement").

Data is both a raw material and an output of our relationships, entertainment, communication, travel, well-being, and financial activity. Nearly all our activities, in this increasingly digital world, add to a breadcrumb trail of data that is of immense value not only to us but also to large organisations looking to sell us products and services. Such data can yield insights not just in terms of what we want, but also when we want it and even how much we are willing to pay for it. Data can allow town planners and local authorities to create smart traffic solutions based on historical and real-time mobility data (see section on "SDG11: Sustainable cities and communities"). It can allow public health experts and epidemiologists to identify patterns and clusters of emerging illnesses and put in place tailored response plans (see section on "SDG 3: Good health and well-being"). It can allow manufacturers to alter their manufacturing schedules in real time to accommodate changes in demand (see section on "SDG 12: Responsible consumption and production"). It can allow an individual to take control of their health journey by monitoring and responding to their bodies' needs using facts and data rather than instinct alone. Just as the internet heralded an information and communications revolution (see section on "SDG 9: Industry, innovation and infrastructure"), we are now experiencing a data-driven decision-making revolution. This revolution will have a dramatic impact on education, educators and students, as well as work and workers.

Implications for Workforce Competencies

The rapid introduction and diffusion of data analytics and AI technologies have resulted in an increased demand for relevant skills. The European Commission has been monitoring members' digital progress since 2014 using the Digital Economy and Society Index (DESI). It tracks European Union (EU) member states' performance across a number of categories, including connectivity, human capital, use of internet, integration of digital technology, and digital public services. A 2022 progress update for the Digital Ireland Framework (Department of Taoiseach, 2022), shows Ireland's continued progress with respect to DESI. Since 2023, DESI has been integrated into the EU's State of the Digital Decade report. Ireland's basic digital skills coverage of 72.9% compares favourably with the EU average of 55.6% (European Commission, 2024). Like our EU counterparts, Ireland is still far below the EU's digital targets for 2030. However, this skills gap is acknowledged in the Expert Group on Future Skills Needs' report, *AI skills: A preliminary assessment of the skills needed for the deployment, management and regulation of artificial intelligence* (Expert Group on Future Skills Needs, 2022).

In relation to higher education, the report recommends the need for specialised AI courses in addition to shorter, flexible courses and microcredentials. In this regard, the authors of this report are broadly in agreement with the expert group. However, the report goes further by providing a holistic framework that incorporates hard and soft skills across big data and AI. Furthermore, the report differentiates between strategic, tactical, and operational data and AI skills (see section on "The data mastery skills matrix"). In the short term, there is a huge demand for specialist operational AI and data skills. However, the descriptions of the roles and responsibilities of such jobs are often vague, contradictory, and prone to the subjective interpretations of employers and would-be employees alike (De Mauro

there is a huge demand for specialist operational AI and data skills.

et al., 2018). Additionally, this short-term emphasis on operational skills may also lead to a deficit of AI project management skills, and a lack of strategic vision. In the data mastery skills matrix, we outline the components of a holistic data and AI mastery approach, which we map against strategic, technical, and operational organisational needs.

Evaluating Current Best Practice in Business Analytics and AI Education

The QS World Rankings for Data Science and Artificial Intelligence evaluates institutions based on five indicators: academic reputation, employer reputation, research citations per paper, H-index, and international research network. Though comparing global data analytics master's programmes is a relatively straightforward exercise (see Table 1), it becomes more difficult to map AI and data analytics programmes according to their institutions' world rankings. This may be accounted for by the wide variation in the way undergraduate education is delivered across different higher education sectors globally. Similarly, many AI and data analytics studies are incorporated into other undergraduate courses, such as information systems and computer science. Alternatively, some universities offer standalone short courses, microcredentials, or elective modules covering these topics. To address this variance, we used the QS subject rankings to identify the top ten universities for data science and AI courses, and then identified specialised data analytics, artificial intelligence, or hybrid data analytics/AI master's programmes. Table 1 shows the top data analytics master's programmes worldwide, while Table 2 displays the top universities for data science and AI programmes based on the QS subject rankings. Following Table 2, courses are evaluated for similarities and differences.

Table 1: QS rankings: Top ten business analytics master's programmes

Ranking	University	Programme	Country
1	Massachusetts Institute of Technology (MIT) (Sloan)	Master of Business Analytics	USA
2	University of California, Los Angeles (UCLA) (Anderson)	Master of Business Analytics	USA
3 *	ESSEC/Centrale Supélec	Master in Data Sciences & Business Analytics	France
3 *	École Polytechnique/HEC Paris	Master of Science in Data Science & AI for Business	France
5	London Business School	Masters in Analytics and Management	UK
6	Columbia Business School	Master of Science in Business Analytics	USA
7	Duke (Fuqua)	Master of Quantitative Management: Business Analytics	USA
8	Imperial College London (Business School)	MSc Business Analytics	UK
9	ESCP Business School	MSc in Big Data and Business Analytics	France
10	IE Business School	Master in Business Analytics and Big Data	Spain

The QS ranking has two institutions sharing the third spot. Unlike QS rankings, the annual US News & World Report's Best Colleges list does rank US undergraduate data science programmes, but it uses a different methodology to the QS rankings which includes philanthropy and financial sources. Stanford University appears at number three for data science in the US News & World Report rankings but does not appear in the QS top ten rankings. We have included the Stanford data science curriculum in our analysis.

Table 2: QS rankings: Top ten universities for data science and artificial intelligence

Ranking	University	Programme(s)	Country
1	MIT	Master of Business Analytics	USA
2	Carnegie Mellon	Master of Science in Artificial Intelligence	USA
3	University of California, Berkeley	Master of Information and Data Science	USA
4	University of Oxford	MSc in Social Data Science; PGDip in Artificial Intelligence for Business	UK
5	Harvard University (Harvard Business Analytics Program)	Master's in Data Science	USA
6	National University of Singapore (NUS)	BSc in Data Science and Analytics; Master of Computing (Artificial Intelligence Specialisation)	Republic of Singapore
7	ETH Zurich	Master in Data Science; Master of Advanced Studies in AI and Digital Technology	Switzerland
8	Nanyang Technological University (NTU), Singapore	Master of Science in Analytics; Master of Science in Data Science; Master of Science in Artificial Intelligence	Republic of Singapore
9	University of Toronto	Master of Science in Applied Computing: Artificial Intelligence; Master of Science in Applied Computing: Data Science; Master of Science in Applied Computing: Artificial Intelligence in Healthcare	Canada
10	Hong Kong University of Science and Technology	MSc in Big Data Technology; MSc in Artificial Intelligence	China

The size of classes differed across all of the courses that were reviewed, and as such it is not possible to compare like for like. Though we did look at mode of delivery for the courses, our focus was on the AI and data analytics curricula. As one would expect from top-ranking universities, all of the programmes evaluated offer a blend of theoretical knowledge and practical skills for data science. Each programme covered essential topics in data analytics, such as business intelligence, machine learning, and statistical analysis. Moreover, all of the courses evaluated prioritised applied skills and real-world application of data analytics and AI. As such, there was a strong emphasis on career pathways in data analytics. The top universities also provided students with access to cutting-edge technical facilities. In addition, the courses were taught by educators and researchers with strong reputations internationally.

There were some differences among the various courses with respect to the curriculum focus. For example, some programmes focused on business analytics or business performance, while others emphasised technical or computational elements. Of note, the only Irish institutions to appear in the top fifty universities for data science and AI courses as ranked by QS are Trinity Business School, Trinity College Dublin (#33) and UCD Smurfit (#44). Clearly, addressing Ireland's international standing should be a strategic priority for third-level institutions. Moreover, there is an opportunity for technological HEIs to play a leadership role in delivering innovative approaches to data science and data-driven decision making.

The Need for Change

Though the rise of big data and AI is generally regarded as a technology revolution, it is essential to also consider the accompanying cultural and social revolution it has launched (see section on "Universal data and AI literacy"). Although data is created through individuals' actions, the data – and the insights such data can yield – can also influence human actions. As our society's capacity to create data increases, so too does the need to store, analyse, and understand it. Conversational AI interfaces, such as ChatGPT, have to some degree democratised data science. At a superficial level, the technology enables those who are not data scientists to engage with data in a natural way and even generate code for analytical problems (Hassani & Silva, 2023). It can assist across all five stages of the data science life cycle: data collection, pre-processing, processing, mining, presentation, and dissemination. As a result, large datasets can be analysed at an unprecedented scale and speed. This has the potential to unlock new insights and assist decision-making across all sectors of the economy (see section on "Interdisciplinary faculty collaboration"). Machine learning algorithms require vast quantities of training data to function. Though many large datasets are freely available under open data initiatives, this is not always the case. Synthetic, but realistic, datasets created by generative AI can be enormously beneficial to experienced and novice data scientists alike.

Data science is no less important now than it was in the 1960s. However, the volume, velocity, and variety of the data has changed. In addition to traditional data science skills, employers need employees – and democracies need citizens – who can understand the strategic impact of data. What is needed is a more multifaceted, holistic conceptualisation of data science that emphasises not just the mechanics of data science but also a deeper understanding of the positive and negative impact that data-driven insights can have.

Data science is no less important now than it was in the 1960s

From Data Literacy to Data Mastery

As discussed in the previous section, advances in technology and our changing relationship with data require a new approach to skill building. The half-life for many technical skills is now five years, and for some can be as low as two and a half years (Tamayo et al., 2023), meaning some technical skills taught at higher education institutions will be redundant in less than five years. This presents us with some unique constraints. In the short term, organisations need highly technical graduates able to bridge the skills gaps for AI and data science. In their book, *A New Culture of Learning*, Douglas Thomas and John Seely Brown argue that higher education is frequently modelled on a "culture of teaching" which assumes well-bounded, finite domains of knowledge that are relatively static. However, such a model is clearly ill-suited to the dynamic, rapidly changing needs of the current data economy. A culture of learning, on the other hand, emphasises practical engagement with the world (Thomas & Seely Brown, 2011). In an environment characterised by change and limitless information and knowledge, a learning-based approach is the most suitable approach.

A key question for higher education institutions remains: How to balance the need to rapidly upskill students while also acknowledging the ephemeral nature of technical skills? How to balance the short-term needs of industry with the wider economic and societal impact of emergent technologies? One way of doing this is to expand the definition of what constitutes data and AI skills, and to teach these skills in a way that emphasises deep engagement with industry and a culture of learning. This requires going beyond the mechanics of data science and incorporating non-technical soft skills. AI is reshaping work at every organisational level. Thus, this report maps key data science and AI skills to the appropriate strategic, tactical, and operational organisational level:

- Strategic level: Focuses on setting out the AI and data analytics vision, including data governance, ethical requirements, investment and cultural change
- Tactical level: Emphasises the management of AI and data analytics projects and their alignment with the organisation's business goals and strategic vision. At this level, there is an emphasis on key performance indicators and optimisation
- Operational level: Requires extensive expertise in AI and data analytics tools. The explicit skills required for the operational level will change frequently. Many papers and government policy documents outline the skills required to

meet employers' AI and data analytics needs. This section outlines a holistic approach, integrating technical skills as well as ethical, critical, and societal perspectives.

Figure 1: Data mastery components

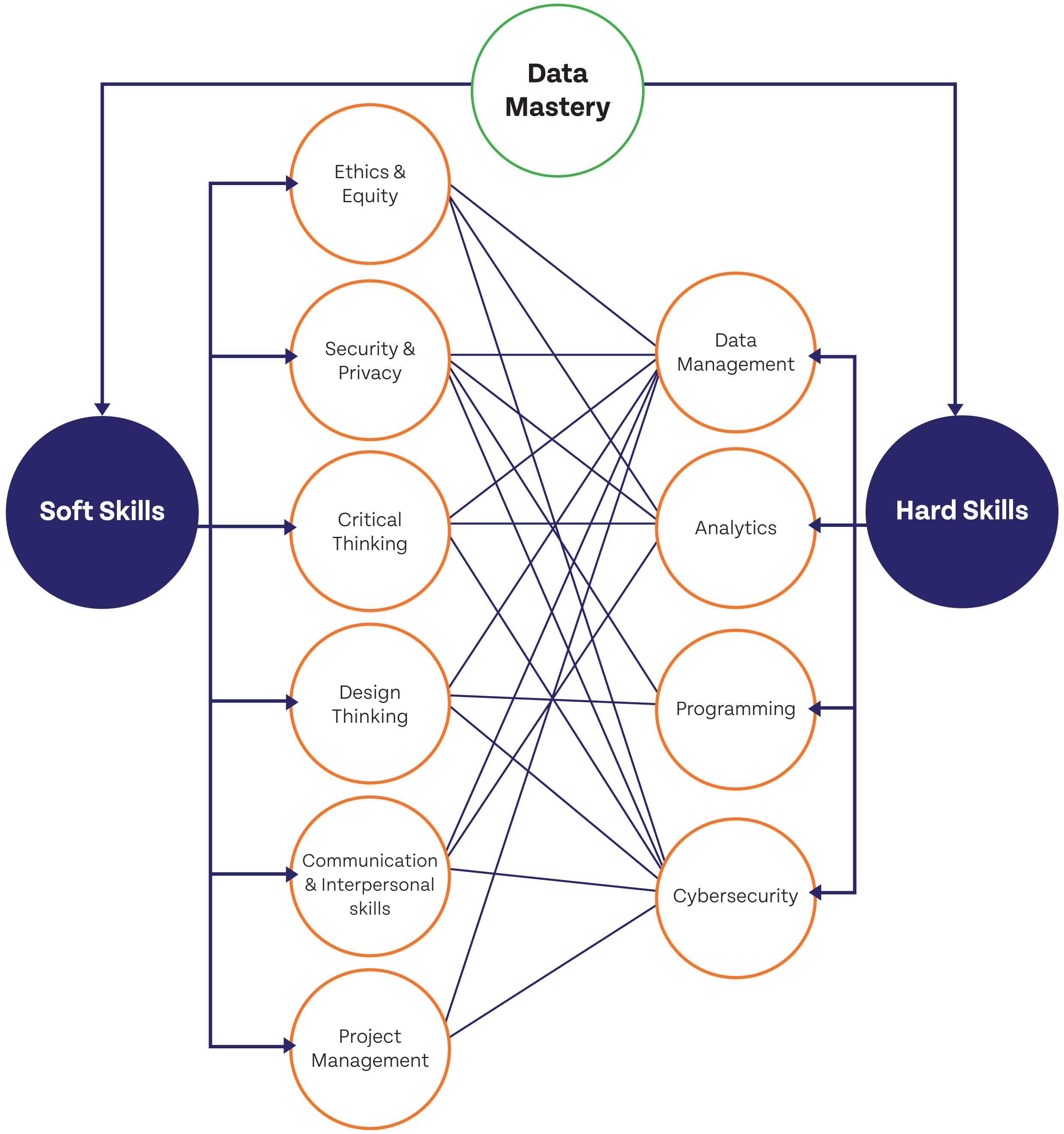


Figure 1 presents the fundamental components of data mastery in higher education. The two main components of data mastery are hard skills, which encompass technical proficiency, and soft skills, comprised of foundational competencies. Hard skills relate to data management, data analytics techniques, programming for data

analytics, and cybersecurity. Soft skills relate to ethics and equity, critical thinking, communication and interpersonal skills, and project management. Combining technical and human skills is not a new approach. ADAPT, the Science Foundation Ireland Research Centre for AI-Driven Digital Content Technology, advocates a holistic socio-technical data literacy framework (Darling et al., 2022). Our skills matrix approach, presented later in Figure 2, also maps skills by organisational level.

This section outlines a comprehensive list of data and AI skills, which are then categorised by organisational level.

Technical Proficiency (Hard Skills)

Hard skills in data management, analytics techniques, and programming are typically included in the core curriculum of most business and data analytics programmes. These skills are essential for students to build a solid foundation in data management, analysis, and computational methods, such as database management, and data quality techniques, data analysis and visualisation, machine learning and advanced analytics, advanced programming for data analytics, and cybersecurity techniques.

Data management: Common data management skills include database management and data quality techniques. Database management techniques encompass the knowledge and expertise required to design, create, maintain, and optimise databases (e.g. SQL, NoSQL databases) so that they store, organise, and retrieve data efficiently. Data quality techniques are methods and practices (e.g. data profiling, data cleaning, and data validation) used to ensure that data is accurate, consistent, complete, reliable, and fit for its intended purpose.

Data analytics: Data analytics skills in statistics and advanced techniques enable data professionals to analyse and interpret complex datasets, uncover meaningful patterns, and provide actionable insights for decision-making. Statistical analytics skills involve applying foundational techniques such as hypothesis testing, regression analysis, and probability theory to uncover trends, relationships, and patterns in data. Advanced analytics skills include using machine learning models, predictive analytics, and multivariate techniques to analyse complex datasets and forecast outcomes.

Programming for data analytics: Skills in programming languages such as Python, R, or SQL empower students to process data, automate tasks, and perform complex analyses. Furthermore, advanced programming for data analytics enables students to create custom code and scripts, enhancing the programme's efficiency and allowing it to address more complex data tasks. These programming skills are critical for students, as they enable them to work independently with data, customise analyses, and adapt to new tools and technologies in the rapidly evolving field of data science.

Cybersecurity: Mastery of data relies on the learner's ability to collect, store, process, and analyse data securely, thus ensuring its confidentiality, integrity, and availability. Moreover, data mastery involves working with large volumes of sensitive information, such as personal, financial, or proprietary organisational data. Common cybersecurity techniques and skills include encryption, network security monitoring, authentication and access control (based on roles or permissions), cloud security, data backup, and disaster recovery, as well as the basic knowledge of security frameworks and standards such as the NIS2 Directive (NIS2, 2024), and the General Data Protection Regulation (GDPR) (2016) (see section on "Security and privacy").

Foundational Competencies (Soft Skills)

Soft skills are as vital as technical knowledge in data mastery. By using them, students are able to navigate ethical challenges, critically assess data insights, and communicate findings effectively. In today's data-driven world, professionals are expected not only to analyse data but also to interpret, explain, and apply it responsibly within various social and business contexts. It is especially critical to be able to take an ethical and equity-focused approach (Alexander et al., 2022), as this will ensure that data-driven decisions are inclusive, fair, and free from biases that could further marginalise vulnerable groups. By prioritising these values, students will be able to critically evaluate the broader social impacts of their work, address systemic inequities, and ensure that data practices align with the principles of justice and accountability. Mastering these soft skills allows students to become not only skilled analysts but also responsible, impactful contributors in their fields. Some foundational soft skills are listed below.

Soft skills are as vital as technical knowledge in data mastery.

Ethics and equity: Considering issues of ethics and equity is essential to achieving true data mastery (Atenas et al., 2023; Şenocak et al., 2024) because data work does not occur in a vacuum – it impacts individuals, organisations, and society as a whole. For example, if not used responsibly, data can amplify biases, potentially leading to discrimination or unfair practices. Prioritising ethics and equity in one's approach will help build public trust and confidence, which transforms data professionals from mere analysts into trusted stewards of information (Garzcarek & Steuer, 2019). Trust is a common thread in the EU Artificial Intelligence Act and is key to the IBM Institute for Business Value's five trends for executives for 2024 (IBM, 2024). Trust is crucial as organisations increasingly rely on data-driven insights to guide decisions, especially in sensitive areas such as healthcare, finance, and governance. By embedding ethical considerations and equity into data practices, professionals not only enhance the credibility of their analyses but also ensure that outcomes are fair, inclusive, and socially responsible. University of California, Berkeley's College of Computing, Data Science, and Society incorporates a number of innovative mechanisms to promote responsible data science. One of these is the Human Contexts and Ethics program, a multidisciplinary taught and led programme that is compulsory for data science majors. Berkeley's College of Computing, Data Science, and Society combines the teaching of hard and soft skills in their curriculum packages, which include code samples, interactive exercises, recorded lectures, and discussion worksheets. Students use these to engage in data science that focuses on ethical issues such as free speech, bias, and algorithmic fairness.

Security and privacy: As outlined above, ethical and moral responsibilities – such as ensuring fairness, equity, and transparency – form a vital foundation for responsible data practices. Alongside these principles, understanding and adhering to legal and compliance obligations is equally critical (Mandinach & Jimerson, 2022). Laws and regulations – including GDPR (2016), the Data Protection Act (Government of Ireland, 2018), and the EU Artificial Intelligence Act (Madiega, 2021) – establish specific standards for data collection, storage, processing, and the ethical use of AI. The rise of AI has also driven updates to both national and EU-level security policies, such as the NIS2 Directive (NIS2, 2024), which enhances cybersecurity requirements for operators of essential services. While regulatory frameworks foster accountability and address risks associated with emerging technologies, they should be taken as minimum requirements rather than comprehensive guides to ethical action. To navigate this complex context, students must be provided with the tools to critically analyse and align their data practices with both ethical values and regulatory frameworks.

Critical thinking: Critical thinking helps data professionals question assumptions and recognise biases in data collection, analysis, and interpretation, which fosters a reflective approach to data use and helps data professionals to critically analyse the data and in doing so consider the security and privacy implementation (Zwitter, 2014). For example, data professionals who employ critical thinking will ensure that individuals' personal data is collected, stored, and processed in compliance with privacy laws (e.g. GDPR) and frameworks such as the UK's Data Protection Act 2018 (Data Act, 2018) and the EU Artificial Intelligence Act, while preventing misuse or unauthorised access to sensitive information (Herschel & Miori, 2017). Likewise, critical thinking may also help professionals navigate the complexities of equitable data use, encouraging them to advocate for inclusivity and fairness by ensuring that underrepresented groups are not marginalised or excluded from the benefits of data insights. By introducing critical thinking, data work is transformed from purely technical tasks into a practice grounded in social responsibility and ethical integrity (King et al., 1990; Rahman, 2019). Clearly, there is a relationship between critical thinking and some of the soft skills discussed. Critical thinking is also an essential skill in helping our digital workforce become data-savvy citizens. Teaching students to evaluate how data is created, managed, and transformed to support knowledge claims is a crucial weapon against misinformation. Critical thinking is thus essential to data scientists and data-literate citizens alike (Wise, 2020).

Design thinking: Most organisations consider the ability of data analytics and AI to reduce uncertainty and randomness to be an advantage. This “analytical approach” is often contrasted with an “intuitive approach” that values creativity and human ingenuity above all else. However, this is a false dichotomy. Design thinking (DT) can be used to bridge the seemingly irreconcilable approaches of intuitive and analytical thinking (Martin, 2009) and thus allow students to cycle between intuitive and analytical models of thinking. DT is an iterative, non-linear approach to problem solving that can help teams to empathise with users, define problems, generate ideas, and deliver solutions through successive prototyping and testing sessions. It represents a foundational skill that can cross disciplinary boundaries. In the context of data analytics and AI, DT can be used to ensure software developers understand users and develop the right solution. Frameworks such as IBM’s Team Essential for AI Course leverage enabled so that technical and non-technical employees can collaboratively create AI solutions.

Communication and interpersonal skills: Effective communication is a vital competency for professionals, especially in data-rich environments where storytelling and presentation skills can bridge the gap between complex data insights and actionable strategies. By developing storytelling and presentation skills, professionals can contextualise data in ways that resonate with diverse audiences (from clients to managers to executives across different sectors), fostering people-centred understanding, conveying technical insights to non-specialists, and advocating for data-driven decisions within organisations (Sundin et al., 2018). By integrating ethical considerations into storytelling and presentation, data professionals build trust and accountability, ensuring that data is not only informative but also responsibly and equitably leveraged to drive positive outcomes (Rieger et al., 2018). Similarly, interpersonal skills are also a vital component of data mastery. Collaboration fosters productive teamwork, ensuring data analysts, IT specialists, and business leaders can align on goals and integrate data insights into actionable strategies. Effectively working in a team can be an important factor in delivering academic and professional success (De Prada et al., 2022). Empathy and active listening skills help data professionals understand the needs and concerns of end users, ensuring that solutions are both relevant and impactful.

Project management: Strong project management skills enable professionals to define clear objectives, allocate resources, and establish timelines for data collection, analysis, and implementation, ensuring that data-driven initiatives are executed efficiently and effectively. Project management also helps coordinate cross-functional teams, ensuring seamless collaboration between data scientists, IT specialists, and business stakeholders. By integrating project management with technical expertise, data professionals can deliver high-quality outcomes that align with organisational goals while optimising time and resource investments. There are many project management frameworks, and the most appropriate one should function in alignment with critical and design thinking strategies, as well as with team members’ interpersonal skills. Frameworks like Agile, Scrum, Waterfall, or Kanban each offer unique advantages depending on project goals, timelines, and team dynamics. For example, Agile and Scrum are well suited for iterative and adaptive processes, supporting critical thinking through continuous evaluation and improvement. Integrating the right tools – such as Trello, Asana, or Jira – further enhances the framework’s effectiveness by streamlining workflows, fostering transparency, and enabling real-time feedback.

The Data Mastery Skills Matrix

Paradoxically, increased automation resulting from AI-assisted decision-making requires more focus on the human element of decision-making. An integrated approach from human data professionals that leverages both soft and hard skills to advance data mastery at every level – from strategic vision and ethical consideration to tactical execution and operational efficiency – is needed. A populated data mastery skills matrix is shown in Figure 2.

Figure 2: Populated data mastery skills matrix

	Soft skills	Hard skills
Strategic	Change management Digital transformation Ethical leadership Data and privacy governance Critical thinking Sustainability strategy Design thinking	Advanced data visualisation Enterprise architecture Cybersecurity strategy AI/machine learning road mapping AI governance Predictive analytics Data value mapping
Tactical	Agile principles Lean Product management Project management Scrum Compliance and regulation Data-driven decision-making Business models	DevOps Cloud infrastructure management Business continuity management Project management tools Business model canvas Predictive analytics Ethics-by-design
Operational	Problem-solving Communication Time management Teamwork User research Design thinking Ethical principles	Python/R/Julia API programming SQL Machine learning Training AI models AI model deployment AI model optimisation Data privacy implementation Statistics Figma Predictive analytics

At the strategic level, an integration of soft and hard skills supports the overall vision and direction for data mastery. Leaders use data-driven insights, backed by hard skills in data management, data quality, and advanced analytics techniques to shape high-level decisions. Additionally, they apply soft skills like critical thinking, ethical awareness, and effective communication to interpret data responsibly. The strategic level focuses on leveraging data and technologies for innovation and competitive advantage, aligning data strategies with the long-term goals of data mastery.

At the tactical level, teams work to translate strategic goals into specific actions and projects. Data professionals apply their hard skills in database management, advanced programming, and advanced analytics techniques to build models and tools that meet specific objectives. Soft skills like problem-solving and adaptability are combined with tactical knowledge such as development methodologies and project management skills which are essential to manage the complexities of projects and to iteratively refine models. The tactical level ensures that data mastery strategies are operationalised through well-defined, measurable actions that propel the vision forward through a combination of soft and hard skills.

At the operational level, the focus is on carrying out daily tasks and processes with efficiency and precision. Hard skills in data visualisation and scripting are essential for automating routine tasks, generating actionable insights, and creating reports that enhance decision-making at the ground level. Soft skills like teamwork, collaboration, and storytelling make data insights accessible and useful for diverse teams. This level emphasises smooth execution, ensuring that data and technologies deliver value consistently, and that daily operations benefit from data-driven improvements.

Delivering Data Mastery in Education

In this section, we discuss the steps required to implement data mastery in higher education, including developing multidisciplinary and interdisciplinary approaches, and aligning with SDGs. The roadmap ensures a strong stock of high-quality graduates to fill current skills needs but also preparing them for the future workforce by training them in key strategic, tactical and operational skills.

Alignment with UN SDGs

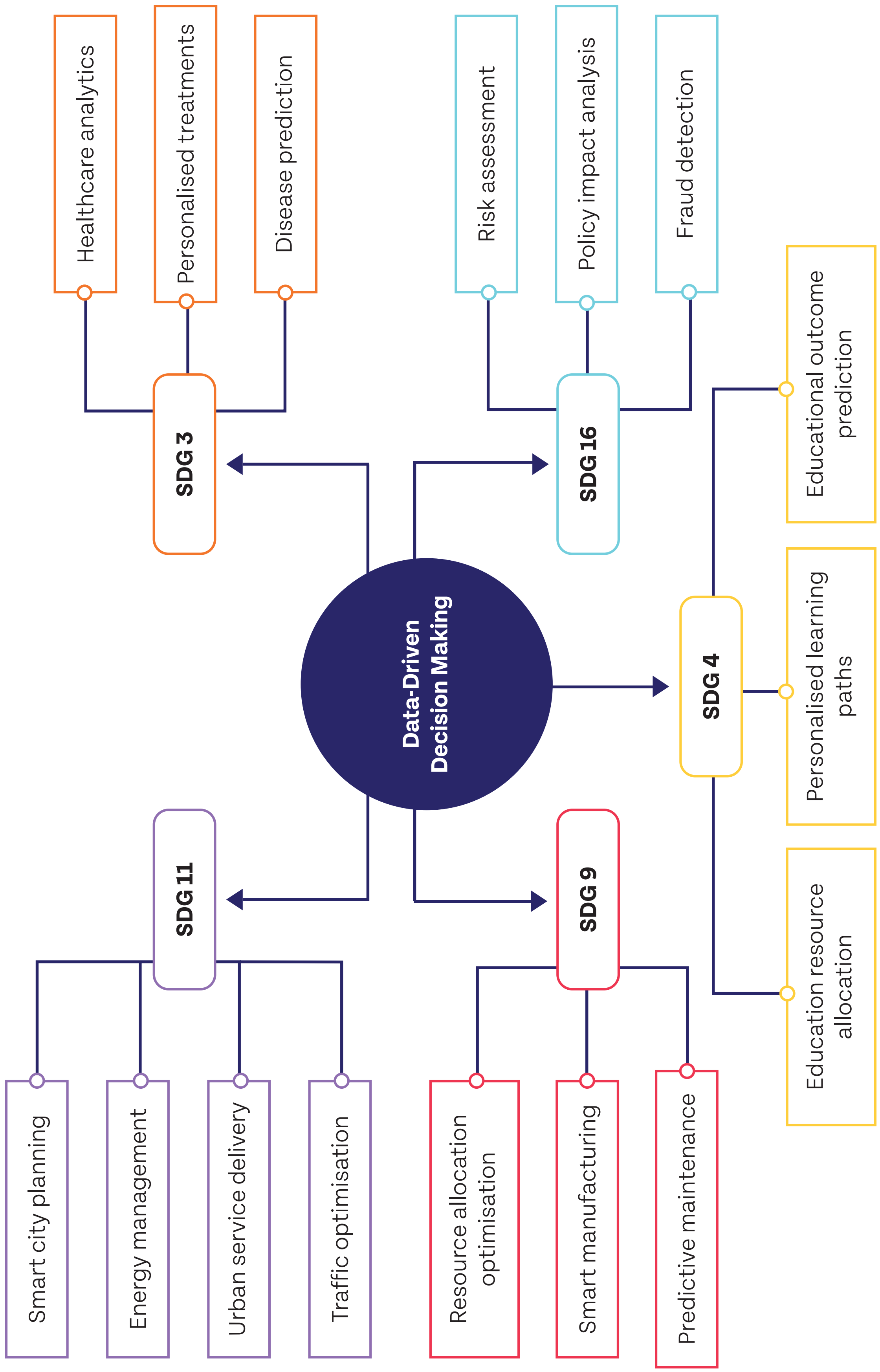
Mapping the future of data-driven decision making to the UN's SDGs offers a strategic way to frame the societal and ethical impacts of AI, big data, and other emerging technologies. The following five SDGs relate specifically to data-driven decision-making:

- **SDG 3:** Good health and well-being – Ensure healthy lives and promote well-being for people of all ages by addressing health challenges such as maternal and child mortality, infectious diseases, and access to universal healthcare and mental health services
- **SDG 4:** Quality education – Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all, emphasising access, gender equality, and the development of skills for sustainable development

  SDG 9: Industry, innovation and infrastructure – Build resilient infrastructure, promote inclusive and sustainable industrialisation, and foster innovation, enabling economic growth and addressing global challenges like connectivity and resource efficiency
- **SDG 11:** Sustainable cities and communities – Make cities inclusive, safe, resilient, and sustainable by improving urban planning, facilitating greater access to housing and transportation, and reducing the environmental impact of urban areas
- **SDG 16:** Peace, justice and strong institutions – Promote peaceful and inclusive societies for sustainable development, provide access to justice for all, and build effective, accountable, and inclusive institutions at all levels

Figure 3 illustrates how data-driven decision-making aligns with these five SDGs, emphasising areas where this transformation can be most impactful.

Figure 3: Mapping subject domain to SDGs



SDG 3: Good Health and Well-Being

Data-driven decision-making is becoming pivotal in healthcare, transforming patient care, resource management, and diagnostics as a result of innovations in big data and AI (Grossglauser & Saner, 2014; Puaschunder & Feierabend, 2019). By focusing on both the hard and soft skills necessary for success in this field, institutions can prepare students to responsibly harness these technologies for health and wellness.

In healthcare, data analytics is used to personalise treatments, predict patient outcomes, and streamline resource allocation (Imran et al., 2021; Wang & Alexander, 2019). For example, AI algorithms can analyse patient history and genomic data to tailor medical treatments, while predictive models help healthcare systems anticipate patient demand and adjust resources accordingly. Real-time data from internet of things (IoT) devices such as wearables further supports these efforts by providing continuous health monitoring, which enhances both preventive care and emergency response. Higher education institutions should introduce these applications of data analytics to students, balanced with considerations of risks and ethics. For example, they should emphasise the potential use cases of such applications while also ensuring they are ethically implemented to ensure patients' privacy and consent are protected, to minimise bias, and otherwise to ensure equitable outcomes (Gooding & Kariotis, 2021; Morley et al., 2020).

Emerging technologies like edge computing and AI have the potential to make healthcare more responsive and accessible. Edge computing allows data from medical devices to be processed locally, enabling faster decision-making in critical scenarios such as emergency care or rural health services. AI-powered diagnostic tools can provide real-time assistance to healthcare providers, supporting faster and more accurate diagnosis. As these technologies evolve, students must understand not only how to work with them but also the ethical implications of doing so, particularly around data privacy and patient consent. Integrating courses that explore the latest advancements in AI and edge computing, along with case studies on healthcare innovation, would enable students to stay at the forefront of health tech.

Hard skills like data analysis, machine learning, and programming are essential for those involved in developing and implementing AI-based solutions in healthcare. Courses in these areas should be coupled with hands-on projects using real or simulated health data to give students practical experience.

Soft skills are equally important. Students need critical thinking abilities to assess the societal impact of health technologies, along with ethical decision-making skills to navigate privacy concerns and patient welfare. Understanding regulatory frameworks like the Digital Health Framework for Ireland 2024–2030, the OECD/WHO Framework for AI in Health (Anderson & Sutherland, 2024; World Health Organization, 2023), and GDPR are also essential, as these govern patient data privacy.

SDG 4: Quality Education

Data analytics is transforming the higher education landscape, allowing institutions to create personalised learning experiences and track student progress more effectively (Blumenstein, 2020; Pardo et al., 2019). AI-driven tools can identify struggling students early, allowing for educators to provide them support in a timely manner, while predictive analytics can help educational administrators allocate resources where they are most needed (Gray & Perkins, 2019; Jokhan et al., 2022). From adaptive learning platforms that adjust to students' skill levels to predictive models that forecast enrolment patterns, data-driven strategies are being employed to enhance student engagement, retention, and overall educational outcomes. Educating students on these applications, and how they can support equitable and quality education, should be a priority for higher education curricula.

> AI-driven tools can identify struggling students early...

As education technology advances, future innovations are expected to play a key role in making quality education more accessible and effective. AI-enhanced learning platforms can help personalise content delivery, allowing students to learn at their own pace. Real-time data from online learning environments can inform immediate feedback, enabling a responsive approach to instruction that adapts to each student's unique needs. Additionally, data-driven systems are expected to enhance administrative decision-making, from optimising curricula to understanding and addressing systemic educational challenges (Teng et al., 2023).

Hard skills such as data analytics, machine learning, and education technology development are foundational, enabling students to design, implement, and assess data-driven educational tools effectively. Providing hands-on experience with datasets, actionable and reflective learning systems, and AI tools prepares students for real-world applications.

On the soft skills side, critical thinking and ethical reasoning are essential, as students must be able to evaluate the societal and personal impacts of data use in education, particularly with regard to privacy and fairness.

SDG 9: Industry, Innovation, and Infrastructure

Higher education institutions play a crucial role in developing students' ability to innovate responsibly within industries and infrastructure such as transportation systems, energy facilities, and telecommunications networks. By integrating courses on AI, data analytics, and edge-cloud computing, higher education institutions can prepare students to contribute to, and eventually lead, advancements in industry efficiency, sustainable infrastructure, and technological innovation.

Data analytics and AI are transforming industries by optimising processes, predicting maintenance needs, and improving resource allocation (Çınar et al., 2020; Zonta et al., 2020). In sectors such as manufacturing, transportation, and energy, predictive analytics can enhance efficiency, while IoT devices enable real-time data collection for immediate decision-making. By understanding these applications, students can appreciate how data-driven strategies support more sustainable, resilient infrastructure and improved industry operations, laying the foundation for impactful careers across various sectors.

Future innovations, such as the combination of edge computing and cloud-based solutions, are expected to revolutionise industrial processes (Chen et al., 2012; Sodhro et al., 2019). Edge computing allows data processing to occur closer to data sources, enhancing speed and reducing latency, which is vital for applications like predictive maintenance in factories and optimising logistics networks. By integrating courses on edge–cloud architectures and predictive analytics, institutions can prepare students to drive innovation that strengthens infrastructure while reducing environmental impact. For students entering industrial and infrastructure roles, a combination of technical and ethical skills is essential.

Hard skills such as data science, systems engineering, and programming are necessary to develop and deploy data-driven solutions effectively. Hands-on experience with data integration, IoT systems, and cloud computing prepares students for practical applications in real-world settings.

Soft skills such as problem-solving, ethical awareness, and sustainable thinking are also crucial, as students need to understand the long-term societal impacts of industrial innovation and infrastructure planning. Emphasising the importance of ethical governance and regulatory compliance, such as adherence to industry-specific data security standards, will further ensure responsible innovation.

SDG 11: Sustainable Cities and Communities

As urban populations grow, the importance of sustainable city planning and management becomes critical. By exploring how technology and data can improve urban life, higher education institutions can equip students with the skills to address pressing challenges in urban development.

Data analytics is becoming foundational to sustainable city planning (Bibri, 2021a, 2021b). Urban planners and policymakers can use data to monitor and manage traffic, optimise public transportation, enhance waste management, and improve emergency response. Introducing students to these applications allows them to understand the complexities of urban management and the potential for data to create positive change in communities.

Future urban innovations will rely heavily on smart city technology and real-time data collection through IoT (Bibri, 2018). These advancements enable cities to respond immediately to environmental or social needs, such as managing air quality or reducing energy consumption during peak hours. By familiarising students with emerging technologies like IoT and edge computing, and their applications in city planning, higher education institutions can prepare students to design adaptable urban systems.

Hard skills with regard to city and community planning include data analytics, environmental science, and urban systems engineering. Providing students with hands-on experience through projects on urban data, smart city simulations, or environmental monitoring tools can enhance their understanding in this field.

Soft skills include cultural awareness, community engagement capabilities, and an ethical approach to data use. Familiarity with regulations like GDPR and local data privacy laws is essential, as these govern citizen data and are critical to fostering trust in data-driven urban management.

SDG 16: Peace, Justice, and Strong Institutions

In the pursuit of SDG 16, higher education institutions should empower students to use data and AI ethically within governance and justice systems, promoting transparency, accountability, equity, and inclusive decision-making. By providing a comprehensive curriculum that emphasises both the power and responsibility of data in institutional settings, higher education institutions must prepare students to foster trust, fairness, and integrity in governance.

Data-driven approaches are reshaping public sector operations and governance, from streamlining administrative functions to enhancing transparency in decision-making (Janssen et al., 2017; Organization for Economic Cooperation and Development, 2019). AI and big data are being used to detect fraud, optimise resource distribution, and inform policy decisions. These applications improve institutional efficiency and accountability but also increase the challenge of AI governance and real-time data transparency. For example, data transparency dashboards allow citizens to monitor public projects and budgets, building public trust.

To support innovation in governance and justice, students need to develop hard skills in data analytics, AI programming, and public policy analysis, equipping them to implement data-driven solutions responsibly. Higher education courses should emphasise skills like data modelling, machine learning, and statistical analysis relevant to policy applications.

Soft skills such as ethical reasoning, public communication, and cultural competency are also critical, enabling students to navigate the complexities of governance and engage equitably with and within diverse communities. An understanding of legal frameworks and compliance, especially in areas like data protection and civil rights, is essential to ensure that governance innovations are both responsible and respectful of citizens' rights (Abiteboul & Stoyanovich, 2019; de Oliveira Silva, 2023).

Universal Data and AI Literacy

One foundational aspect for data mastery is to design universal courses or modules on data literacy and AI literacy that are accessible and relevant for all students, regardless of their educational background. By introducing core data and AI concepts to students in fields like humanities, business, and social sciences, these courses can ensure that every student has a basic understanding of data. As an example of best practice, University of Florida created an AI Across the Curriculum programme that gives every single undergraduate student, irrespective of discipline, the opportunity to engage and learn about AI (Southworth et al., 2023). AI certification also gives University of Florida graduates a competitive edge in the marketplace. To be truly universally accessible, AI and data literacy courses should consider adopting open-access principles, which would entail open licensing and free availability of course materials. The advantages of this approach include that it would democratise data literacy education, foster collaboration across institutions, and ensure that diverse perspectives are integrated into teaching resources.

Policy Labs and Regulatory Sandboxes

Policy Labs are innovation hubs designed to improve policymaking processes through creative, participatory, and evidence-based approaches. They typically bring together multidisciplinary teams to explore complex policy challenges and identify practical solutions by integrating design thinking, foresight, behavioural insights, and systems thinking. Policy Labs can create a participatory and adaptive environment that addresses challenges and opportunities in AI or data governance, ensuring ethical, equitable, and effective frameworks. Regulatory sandboxes could provide the public sector, academics, and students with a mechanism to collaboratively uncover the shortcomings and limitations of new policy and even create new policies.

Policy Labs can create a participatory and adaptive environment...

A Data Mastery Matrix Approach

Though the skills that comprise the data mastery skills matrix (shown in Figure 2) will change, the template (see Figure 4) provides a holistic lens for future skills needs planning. To implement the data mastery matrix, higher education institutions need to balance specialist technical skills and competencies with foundational hard and soft skills across all organisational levels.

Specialist Technical Competencies

For students pursuing data-intensive careers, it is crucial to take more advanced courses which dive deeper into specialised skills such as machine learning, data engineering, and big data analytics. As data technologies evolve rapidly, it's important for these advanced courses to stay current with emerging trends, tools, and methodologies. Offering up-to-date technical content ensures that graduates are well-prepared to meet industry demands, work with the latest technologies, and adapt to changes in the data landscape. This emphasis on cutting-edge knowledge equips students not only with theoretical understanding but also with the technical competence necessary to excel in a fast-paced, data-driven environment. Industry advisory boards can be used to provide insights about skills needs and emerging trends, which can be used to inform new course design. AI could also be used by higher education institutions for trend analysis and labour market analytics.

Figure 4: Data mastery skills matrix template

	Soft skills	Hard skills
Strategic		
Tactical		
Operational		

Delivering skills that meet the rapidly changing demands of the labour market requires teaching staff to be equipped with the skills to teach emerging skills and methodologies. Providing additional mechanisms for continuous professional development will ensure that lecturers can keep up with these changes and maintain the relevance of their curricula. Standardised training and boot camps can be supplemented by hiring industry partners as staff, and by hosting hackathons and collaborative research projects. Such mechanisms will expose staff to cutting edge technologies and industry needs. Collaborative research projects with industry are commonplace in higher education. Indeed, exposing students to cutting edge research is an important part of the connected curriculum. However, encouraging academic staff to embed with industry partners to improve the teaching of technical subjects is unique.

Balanced Hard and Soft Skills

A well-rounded data mastery programme incorporates both hard and soft skills, recognising that data literacy is a holistic concept, extending beyond solely technical ability. Hard skills, such as programming, data structuring, and analytical techniques, are essential for working directly with data. However, soft skills like communication, critical thinking, and ethical awareness are equally important. These skills enable students to present data insights clearly, make ethical decisions regarding data use, and collaborate effectively in interdisciplinary teams. By embedding these competencies into course offerings, programmes can foster professionals who are technically skilled, ethically aware, and effective communicators – all highly valued qualities in any field that relies on data.

Traditionally, higher education institutions have not been agile when it comes to updating curricula. However, without responsive curriculum management and approvals processes, efforts to modernise are doomed to failure. Given the half-life of highly technical subjects and skills, current processes are not fit for purpose. Once again, AI could be used to automate routine paperwork and prioritise job applications based on factors such as skills perishability and employment demand. There is an opportunity to pilot new programmes using expedited approvals processes and provisional accreditation. However, responsiveness should not be jettisoned at the expense of rigour. After-action reviews of both new programmes and the review processes itself will lead to better outcomes. Microcredentials represent another innovative way to address skills gaps. However, microcredentials require high levels of resources to implement and are dependent on accurate skills audits to demonstrate value (Carroll et al., 2023)[1]. In this respect, microcredentials and improved curriculum management are not mutually exclusive.

Industry and Community Engagement

Practical experience and industry insights are other vital components of multi-disciplinary data mastery. By incorporating internships, co-op programmes, and industry-led projects into the curriculum, students gain hands-on experience with real-world data challenges. Such opportunities provide invaluable exposure to industry expectations and practices, helping students build the problem-solving skills and adaptability needed for data-intensive roles. Industry collaboration also ensures that academic programmes remain relevant

[1]See Belshaw et al. (2024), also in the National Digital Learning Network report series, for further exploration of microcredentials in higher education.

and responsive to actual market needs, enhancing graduates' readiness for data analytics roles and improving their employability.

Next practice should incorporate mechanisms to make research accessible to the wider community. Initiatives such as UCC's Community Academic Research Links (CARL), or the Atlantic Technological University's community-based research projects, connect researchers with community groups to tackle local issues. A similar programme for data-driven decision-making could be implemented. Students could work with community members and academic supervisors to tackle data challenges. For example, community organisations might have amassed large amounts of data but lack the technical expertise to unlock insights. This would be an opportunity for students to get access to real datasets to practice data science. A similar model could be implemented with small- to medium-sized enterprises.

In the domain of AI and big data, we have seen a shift in the traditional relationship between industry and academia. Much of the science around data analytics and AI is being driven by industry, which has the computing power, staff, and financial resources to scale large language models. In the early days of computing, companies would have had to access computing resources from universities. Clearly, this is no longer the case.

Interdisciplinary Faculty Collaboration

Though our higher education institutions may not have the financial or computing resources of some private sector companies, they do possess some advantages. One advantage is the availability of researchers and staff with a huge variety of different skills. Encouraging interdisciplinary collaboration among faculty members enhances the development of multi-disciplinary data mastery. Faculty from various departments bring unique perspectives to data issues, enriching the curriculum and broadening the scope of data literacy education. When instructors in business, computer science, social sciences, and other fields collaborate on data courses, students benefit from a curriculum that is diverse in its applications and approaches. This interdisciplinary approach ensures that data literacy is not isolated within technical disciplines, but rather is a core competency across multiple fields, fostering graduates who are equipped to handle data in complex, multi-faceted environments. The democratisation of data analytics technologies, facilitated by generative AI, means that data analytics is being applied in an ever-increasing variety of settings and disciplines. Our higher education institutions have a huge opportunity to lead the way here. This interdisciplinary approach should also extend between institutions. In the face of increasing financial constraints in the higher education sector, the sharing of knowledge and resources is crucial.

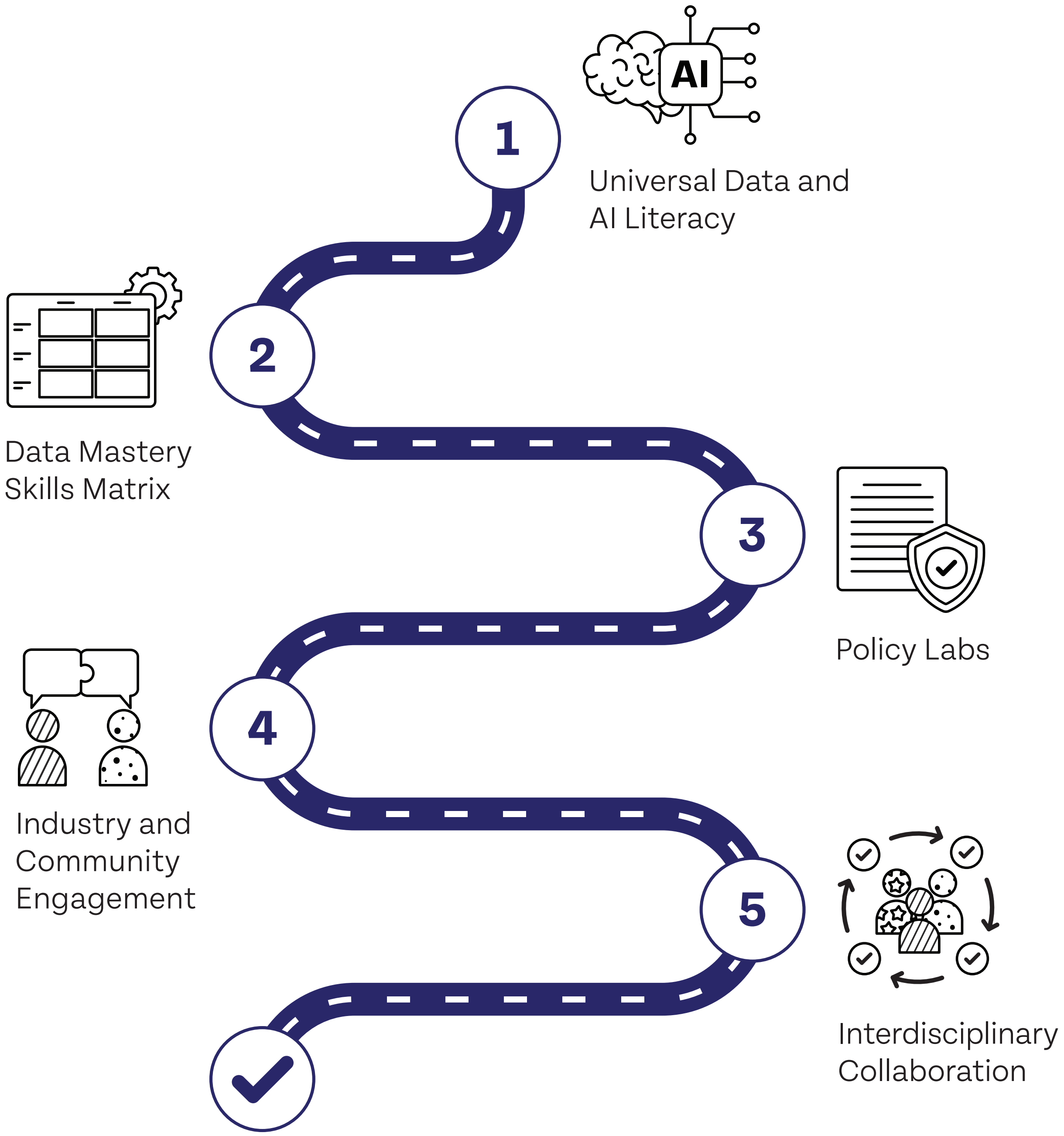
Conclusion: A Roadmap for Data Mastery in Higher Education Institutions

Much of the recent government and education policy on future skills needs focuses on the production of T-shaped graduates. The term "T-shaped talent" was popularised by the former CEO of IDEO, Tim Brown. The phrase was used to describe how IDEO hires employees with broad skills across multiple domains, but who also possess a deep expertise in one or more particular areas of expertise (Conley et al., 2017; Demirkan & Spohrer, 2015). However, Matthew J. Daniel, Senior Principal of Talent Strategy at Guild Education, suggests that, with increasing career fluidity and worker mobility, the T-shaped approach is no longer applicable (Daniel, 2020). This, coupled with the decreasing half-life of technical skills, suggests that there is a need for a new metaphor.

The data skills matrix approach recognises the interdependency of hard and soft skills, and the variability of skills durability, as well as the importance of planning for future needs. For example, changes in data-driven decision-making, such as those facilitated by AI, could require skills in machine learning (operational), ethics-by-design (tactical), and AI governance (strategic). Traditionally, undergraduate programmes in higher education have focused on operational skills, while master's programmes have targeted tactical and strategic skills. However, the pace of technological change means that this approach is no longer practical. All courses will need to deliver a mix of hard and soft skills across strategic, tactical, and operational levels if we want to shape our digital future, rather than respond to it.

As discussed in the introduction, highly skilled workers are needed to grow the data economy. Data literacy may be enough to help sustain the data economy, but data mastery will be required to shape it. This will not be easy. Figure 5 illustrates the mechanism, or critical success factors, that will be necessary to build an environment that can deliver data mastery.

Figure 5: Data mastery skills roadmap



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Success Vignettes

Central Statistics Office

The Central Statistics Office (CSO) provides independent statistics about Ireland's society, economy, and environment. These statistics are available to everyone, including the Irish state. They are designed to facilitate "evidence-informed decision making". The data provided by the CSO is prepared and verified to a very high standard. CSO data serves as a high-quality source to inform policy and business at all levels, but also as a trusted source to explore decision-making scenarios in the lecture room.

Atlantic Technological University

Atlantic Technological University offers a module on data-driven decision-making, defined as "using facts, visualisations, metrics and data to guide strategic business decisions that align with your goals, objectives and initiatives". This module explores how different decision theories, tools, and data analytical and visualisation approaches can improve organisational performance. It includes learning outcomes such as researching and synthesising information to justify data-driven decision-making, critically analysing data using data analytic techniques, and formulating recommendations using decision theory. The module uses a broad range of delivery and learning techniques.

Netflix

Netflix drives its content delivery with extensive use of data-driven decision-making, analysing viewer data to make personalised recommendations. Metrics such as watch time, date, location, and user interactions are gathered and analysed. As a result, Netflix has achieved an 80% success rate with users following its recommendations. Netflix uses this approach to drive its business goals of increased revenue and acquisition and retention of subscribers. This is an example of how the platform itself provides essential data to the business alongside providing services to consumers.

Hewlett-Packard

In 2015, Hewlett-Packard split into Hewlett-Packard Enterprises and HP Inc. to address the company's sprawling workforce and product portfolio. The decision to streamline company operations was made to allow Hewlett-Packard to compete with its more agile competitors. The decision and composition of the reorganisation effort was guided by comprehensive operating data and forecasting models. This demonstrates how data-driven decision-making can change organisational structure and strategic vision.

Zara

Fashion retailer Zara uses predictive analytics for inventory management. Data-driven decision-making allows the company to respond quickly to emerging fashion trends. Zara can adjust stock levels based on models which predict the popularity of items. It is estimated that Zara has reduced its unsold inventory by approximately 25%.

National
Digital
Leadership
Network

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