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Aligning Higher Education with Workforce Competency Requirements in Data Science and Electric Vehicles: A Systematic Literature Review

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Abstract

Rapid digitalisation and decarbonisation are reshaping the relationship between higher education and work, creating pressure for curricula to respond to emerging workforce competency requirements without becoming narrowly tool-driven. This systematic literature review examines data science and electric vehicle (EV) industries as comparative high-tech sectors within the new economy, representing the digital and green transitions, respectively. Using a PRISMA-informed protocol, 40 peer-reviewed journal articles published between 2010 and 2025 were synthesised: 20 from data science and 20 from EV-related fields. The analysis was interpreted through graduate employability and university–industry collaboration perspectives to move beyond a simple inventory of technical skills. Six competency clusters were identified in each domain, together with six cross-cutting capabilities: systems thinking, digital fluency, communication, problem solving under uncertainty, responsibility, and lifelong learning. Four mechanisms for higher education–industry alignment were also identified: competency-based curriculum mapping, authentic and work-integrated learning, recurring employer participation, and flexible upskilling pathways. The comparison shows that both sectors challenge discipline-bound educational models because workplace performance increasingly depends on the integration of technical knowledge, judgement, communication, ethics, and adaptation. The study proposes a higher education–industry competency alignment framework and discusses implications for graduate employability, equitable access to applied learning, institutional governance, and workforce development in data science and the electric vehicle industry.

Keywords: graduate employability; curriculum reform; digital transition; green transition; work-integrated learning; interdisciplinarity

1. Introduction

Digitalisation and decarbonisation are impacting on jobs and technologies, as well as the relationship between universities, employers and students. Universities are expected to provide students with not only an ability to adapt to an evolving workplace but also with the capacity for lifelong learning, ethical understanding, critical and ethical reasoning and durable knowledge. This is especially relevant to technology-driven fields where the nature of the work may evolve more rapidly than the existing curriculum structure.

Electric vehicles (EVs) and data science are two examples of contrasting yet equally interesting transitions. The transition to EVs is an industrial and green transition requiring the convergence of mechanical, electrical, battery, charging, sustainability, diagnostics, and software knowledge with an understanding of the entire vehicle. Data science is a digital transition that requires a convergence of decision-making, evidence, algorithms, software, data and work structured around data. In both fields, employability is based on a combination of technical and transferable skills instead of just fluency in a specific tool. Thus, this comparison can identify a common issue that exists across two different technological domains and can explore how higher education can best equip students to be adaptable, interdisciplinarily capable, responsible, technically strong and capable decision makers.

This trend is well exemplified in the data science research literature. In the earlier publications in journals data science was discussed in terms of data-driven decisions and prediction (Dhar, 2013; Provost & Fawcett, 2013). More recently, reproducibility, communication, ethics and fairness, software practice, data curation, and visualisation have all received greater attention (De Veaux et al., 2017; Donoho, 2017; Hardin et al., 2015; Mehrabi et al., 2021). The educational implication is that a curriculum centred only on algorithms or programming cannot represent the full range of capabilities required for professional practice.

The EV literature reveals a parallel broadening of occupational requirements. Beyond assembly and conventional automotive servicing, EV-related work requires knowledge of batteries, battery management systems, charging infrastructure, thermal management, power electronics, software-enabled control, diagnostics, standards, and safety (Hannan et al., 2017; Xiong et al., 2018; Yilmaz & Krein, 2013). These changes create pressure on universities and technical and vocational education and training (TVET) providers to integrate previously separated bodies of knowledge and to provide more authentic opportunities for practice.

Thus, the central issue is not merely a lack of specific skills within the workforce. Rather, there is an alignment issue across the required skills in the workforce, the

educational offerings, graduate employability, the higher education institution itself, the role of industry in the educational process, availability of experiential education opportunities, and the ability of education systems to adapt to technological advancement. This research seeks to address this issue through an analysis of the skills present in both data science and electric vehicles research and the application of these findings to educational policy, institutional practice, and the higher education–industry relationship. Specifically, these two advanced technological fields are used as two contrasting examples of the new economy in order to determine field-specific and cross-cutting skills needed, and institutional approaches to addressing the green and digital transformations through higher education.

2. Theoretical and Literature Background

2.1 Graduate Employability and University–Industry Alignment

A graduate employability focus is used in this study that acknowledges employability as more than a set of technical competencies. Tomlinson (2012) suggests that graduate employability is influenced by the evolution in the link between higher education and the labour market. The graduate capital approach highlights the assets that graduates create and utilise in the transition to the labour market (Tomlinson, 2017). In the context of EV and data science education this approach not only highlights technical knowledge, but also experience, adaptability, identity, networks, translation of learning to the workplace, communication and resilience.

The study also looks at university and industry collaboration through an institutional perspective. The Triple Helix model views innovation as arising from interactions among government, industry and universities rather than occurring within a single institution (Etzkowitz & Leydesdorff, 2000). In terms of education, this view suggests that relevance is created in collaboration between education standards, policies, work-integrated learning, lifelong learning, employer input and industry needs. However, this does not mean that universities only provide training for immediate employment within an organisation. Universities also have a role in providing transferable attributes such as ethical practice, learning ability and judgement that are important despite fluctuations in specific technologies.

2.2 Comparative Rationale: High-Tech Industries in the Digital and Green Transitions

Comparison between EV industries and data science fields is made purposefully as both are applications of the same type of transition but in different technological forms. Data science is heavily software and data-driven while an EV is a physical electrified system. Both domains however are becoming more and more about system integration, interdisciplinary work, fast evolving new technologies, ethical decision-making, digital tools and technologies.

This comparative logic also addresses a broader educational question. If similar cross-cutting competencies appear in two sectors with very different technical knowledge bases, those competencies are less likely to be artefacts of a single

occupation and more likely to represent general requirements of high-tech work in the new economy. The comparison is therefore used as an analytical strategy for examining how higher education can respond to the combined digital and green transitions, rather than as an attempt to treat the two industries as technically equivalent.

2.3 Domain-Specific Competency Literature

Competence is generally understood as the ability to perform effectively in a given context. In technology-intensive industries, however, competence is more than just the ability to perform; the work that must be done is usually non-routine and based on problems that require solutions through teams of workers with different skills and knowledge. In these situations, competence is best understood as including skills beyond technical skills - skills like communication, collaboration, adaptability, and ethical reasoning. These skills are especially important in high-growth industries in which technologies develop at a rapid rate.

Competence frameworks for data science grew up as a response to the understanding that teaching statistics to data science students or teaching programming to data science students is not a complete curriculum. Authors like Hardin et al. (2015) have called for teaching students to think with data, while others like De Veaux et al. (2017) have proposed guidelines for curricula that include mathematics, statistics, data management, computational thinking, and communication. Later research studies have proposed additional requirements for data science curricula, such as learning how to use reproducible programming practices (Mehrabi et al., 2021; Reinhart & Genovese, 2021; Ridgway, 2016).

The literature that has developed regarding electric vehicles (EVs) has developed along a different path altogether. For instance, one of the early focuses of the literature regarding EVs is upon the technical aspects of those vehicles, such as their charging modes (Lu et al., 2013; Tie & Tan, 2013; Yilmaz & Krein, 2013). More recent literature, however, has focused upon the technical aspects of the batteries that are utilised within those EVs, such as battery health monitoring (Xiong et al., 2018), thermal management (Zhang et al., 2022), charging infrastructure for EVs (Mastoi et al., 2022), and the planning of EV charging infrastructure (Liu et al., 2021; Micari et al., 2017). Beyond publishing research that discusses the technical aspects of EVs and their batteries, many of these technical studies also indicate the skills that are required to fulfil those technical aspects of the EVs. Thus, while the studies may not utilise the term “workforce” itself within their publications, they do help to reveal information regarding the skills of the workforce that is required to support the growth of the EV sector.

In both domains, labour market research demonstrates signs of hybridisation. Employers do not seek workers who merely understand the tools of the trade, but those who can apply those technologies to various problems that may arise within the field. Within data science, this means applying statistical knowledge to decision-

making. Within the electric vehicle domain, this means connecting various components of an electric vehicle. For higher education, this means redesigning curricula to emphasise industry problems, transferable skills, work-integrated learning, and industry input to ensure that educational programmes are aligned with the demands of industry. The convergence of these two fields, therefore, indicates the need for a review of both fields that is broad enough to consider each domain separately yet focused enough to consider the alignment of education with industry within each domain.

3. Research Objective and Research Questions

3.1 Research Objective

The objective of this research is to systematically identify, compare, and synthesise workforce competency requirements in the data science and electric vehicle industries and to analyse the pedagogical and institutional mechanisms through which higher education and training systems can be aligned with these evolving requirements. The study therefore treats competency alignment as both a curricular issue and a socio-institutional problem involving graduates, employers, education providers, and public policy.

3.2 Research Questions

To achieve the objective, the study addresses the following four research questions:

RQ1: What workforce competency requirements are emphasised in the data science literature?

RQ2: What workforce competency requirements are emphasised in the electric vehicle literature?

RQ3: What cross-cutting competencies connect these two domains, and how can they be synthesised into an integrated framework for workforce development?

RQ4: What pedagogical and institutional mechanisms can align higher education curricula and training systems with the workforce competency requirements of data science and the electric vehicle industry?

4. Methodology

4.1 Review Design

A systematic literature review (SLR) was carried out using PRISMA 2020 guidelines (Page et al., 2021). There were six steps in the review process. This included selection of databases, creation of competence and sector-specific searches, definition of inclusion criteria, screening of titles and abstracts and then full text screening according to inclusion criteria. Finally, data extraction and thematic synthesis was carried out. A systematic literature review was chosen due to the scattering of the literature across engineering, energy systems, computing, statistics, workforce,

education and other sectors. Rather than attempting to pool data and estimate effect sizes, the aim was to detect common trends in competencies and the relationships between education and industry across these diverse studies. For this reason, a thematic and narrative synthesis was considered suitable (Thomas & Harden, 2008). Methods have been described transparently including: databases searched, Boolean operators used, date range of searches, eligibility and exclusion criteria, number of items screened and extracted data, and coding processes. These components allow the methodology of the review to be replicated.

4.2 Search Strategy and Information Sources

Searches were conducted in Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar to capture literature across engineering, data science, education, and applied technology. Search strings combined domain terms with competency, workforce, curriculum, education, training, and employability terms. For the data science stream, terms included data science competencies, data science workforce skills, data science curriculum, analytics employability, and data science education. For the EV stream, terms included electric vehicle skills, EV workforce training, battery management skills, charging infrastructure competencies, and electric mobility technical education. Database-specific adaptations retained the same conceptual blocks shown in Table 1. The searches were completed and last updated in May 2026.

Table 1. Boolean search strings used in the review

Domain	Boolean search strings
Data science	((("data science" OR "data analytics" OR "machine learning" OR "artificial intelligence" OR AI) AND (competenc* OR skill* OR workforce OR employability OR curriculum OR education OR training) AND ("data literacy" OR "computational thinking" OR "model evaluation" OR "responsible AI" OR ethics))
Electric vehicles	((("electric vehicle*" OR EV OR "electric mobility" OR "battery electric vehicle*" OR "plug-in electric vehicle*") AND (competenc* OR skill* OR workforce OR training OR employability OR curriculum) AND ("battery management system*" OR BMS OR "charging infrastructure" OR "high-voltage safety"

	OR diagnostic* OR maintenance OR "power electronics"))
Cross-cutting skills	((("systems thinking" OR "interdisciplinary teamwork" OR communication OR employability OR "digital literacy" OR "lifelong learning" OR "human-machine collaboration" OR "technical education") AND ("data science" OR "electric vehicle*" OR EV OR "electric mobility" OR "AI skills" OR workforce OR training OR competence*))

4.3 Eligibility Criteria

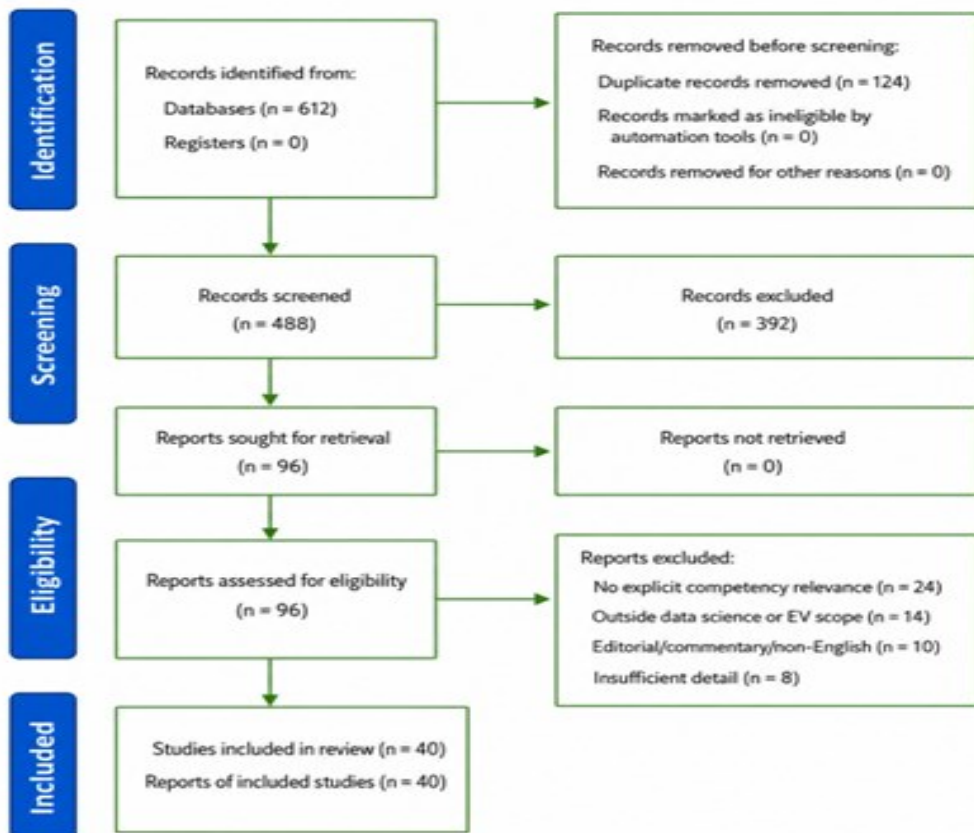
The review of existing literature on the topic was limited to studies published between 2010 and 2025. Inclusion criteria were: (1) the publication focused on data science, analytics, electric vehicles, batteries, charging systems, or closely related workforce/training domains; (2) it discussed competencies, skills, curriculum, technical capacities, or workforce readiness either explicitly or in a way that could be directly mapped to work requirements; (3) it was a peer-reviewed journal article with substantive analytical content; and (4) the full text was available in English. Exclusion criteria were: (1) publications with no meaningful relevance to workforce competencies; (2) purely promotional or news items; (3) duplicate records; and (4) publications lacking sufficient detail for competency extraction.

4.4 Study Selection and PRISMA Screening

Study identification, screening, eligibility assessment, and inclusion were documented in accordance with PRISMA 2020 reporting guidance (Page et al., 2021). The initial search yielded 612 records. After removing 124 duplicates, 488 records remained for title and abstract screening. Screening excluded 392 records that were out of scope, non-scholarly, too general, or lacking competency relevance. Ninety-six reports were assessed at full-text stage. Fifty-six of these were then excluded for one or more reasons: no explicit competency contribution (n = 24), outside the specific scope of data science or EV workforce development (n = 14), non-journal, editorial/commentary, or non-English status (n = 10), or insufficient full-text detail (n = 8). The final sample consisted of 40 studies: 20 in the data science stream and 20 in the EV stream. All 40 included studies were peer-reviewed journal publications; books, reports, preprints, professional-magazine articles, and conference proceedings were excluded from the review corpus. Thus, the study selection process ensured that only studies related to the competencies within the data science and electric vehicle industries were utilised in the review. Figure 1 presents an overview

of the selection process that leads to the 40 studies that were ultimately included in the qualitative synthesis.

Figure 1. PRISMA framework used for the systematic literature review.



4.5 Data Extraction and Coding

Data extraction used a structured matrix containing six fields: author(s) and year, domain, study focus, study type, competency contribution, and implications for curriculum or higher education–industry alignment. Coding proceeded in three stages. First, competency statements were coded inductively within each study. Second, similar codes were grouped into broader domain-specific and cross-cutting competency themes. Third, statements concerning curriculum, pedagogy, employability, employer expectations, work-integrated learning, and workforce preparation were coded to identify alignment mechanisms. The coding process therefore moved from descriptive evidence to analytical themes while retaining traceability to the included studies, consistent with thematic synthesis principles (Thomas & Harden, 2008).

Workforce competency requirements were coded when a study explicitly described a skill, capability, training need, or curriculum requirement, or when its technical analysis identified knowledge and practical capabilities directly necessary for professional performance. This latter approach was particularly relevant to the EV stream, in which several technical and infrastructure studies did not use workforce terminology but provided evidence concerning battery systems, charging infrastructure, diagnostics, software control, testing, maintenance, and safety. These inferred competency requirements were retained only when a direct connection to occupational or educational capability could be established.

4.6 Synthesis Procedure

The synthesis produced six competency clusters in data science—problem framing and stakeholder understanding; data acquisition, preparation, and quality management; analytical and modelling competence; communication and visualisation; coding, software, and deployment readiness; and ethical, collaborative, and adaptive capability. These clusters are visually summarised in Figure 2 and supported by the evidence presented in Table 2.

It also produced six competency clusters in EV work—vehicle systems and systems integration; battery systems competence; charging infrastructure and grid interface; diagnostics, monitoring, and software-enabled control; installation, testing, and quality assurance; and maintenance, troubleshooting, and safety culture. These clusters are visually summarised in Figure 3 and supported by the evidence presented in Table 3.

In addition, six cross-cutting competencies common to both fields and four higher education–industry alignment mechanisms were identified. The six cross-cutting competencies are presented in Figure 4 and Table 4, while the four higher education–industry alignment mechanisms are summarised in Table 6. The synthesis was reviewed iteratively to ensure that the categories were conceptually distinct yet broad enough to accommodate variation across studies.

5. Descriptive Profile of the Included Studies

The final corpus of 40 studies was equally distributed between the two domains, with 20 studies contributing evidence on data science workforce competency requirements and 20 contributing evidences on EV workforce competency requirements. The data science studies primarily examined curricula, competencies, pedagogy, professional practice, literature reviews, and specific capabilities. In contrast, the EV stream contained predominantly technical reviews, infrastructure studies, systems research, and a smaller number of training-related publications.

6. Results and Thematic Synthesis

6.1 Data Science Workforce Competency Requirements

The thematic synthesis has identified six clusters of competencies within the field of data science. Figure 2 presents the relationship between these competency clusters, and Table 2 presents the specific data science competencies within each cluster and the research studies that helped to identify those competencies. The six competency clusters that have been identified through the analysis of the 20 data science journal studies are: problem framing and stakeholder understanding; data acquisition, preparation, and quality management; analytical and modelling competence; communication and visualisation; coding, software, and deployment readiness; and ethical, collaborative, and adaptive capability. These competency clusters provide a structure for curricula to cover the entire life cycle of data science and data engineering activities, from the initial framing of problems through to ethical and collaborative competency requirements of data scientists.

Figure 2. Data Science Workforce Competency Framework.



Table 2. Data science competency clusters derived from the review

Cluster	Illustrative capabilities	Representative studies
Problem framing and stakeholder understanding	Clarify objectives, define analytical questions, align analysis with organisational problems.	Blei & Smyth (2017); Provost & Fawcett (2013); Waller & Fawcett (2013)

Data acquisition, preparation, and quality management	Clean, integrate, sample, document, and assess the suitability of data.	Hardin et al. (2015); Baumer (2015); De Veaux et al. (2017)
Analytical and modelling competence	Apply statistics, machine learning, validation, forecasting, and interpretation.	Donoho (2017); Cao (2017); Reinhart & Genovese (2021); Guidotti et al. (2018)
Communication and visualisation	Create dashboards, reports, stories, and explanations for non-technical users.	Hicks & Irizarry (2018); Dogucu et al. (2025)
Coding, software, and deployment readiness	Program in relevant languages; build reproducible workflows; support deployment.	Reinhart & Genovese (2021); Crisan et al. (2021); Nolan & Temple Lang (2010)
Ethical, collaborative, and adaptive capability	Work in teams; address privacy and fairness; engage in lifelong learning.	Saltz & Dewar (2019); Mehrabi et al. (2021); Ridgway (2016)

6.2 Electric Vehicle Workforce Competency Requirements

The thematic synthesis leads to the identification of six clusters of competencies within the EV workforce. Figure 3 displays the EV competency clusters, and Table 3 presents the specific EV workforce capabilities identified or inferred from the included studies.

Figure 3. Electric Vehicle Workforce Competency Framework.

ELECTRIC VEHICLE WORKFORCE COMPETENCY PATHWAY	
Vehicle systems and systems integration	
Battery systems competence	
Charging infrastructure and grid interface	
Diagnostics, monitoring, and software-enabled control	
Installation, testing, and quality assurance	
Maintenance, troubleshooting, and safety culture	

The six competency clusters derived from the 20 included EV-related journal studies are: vehicle systems and systems integration; battery systems competence; charging infrastructure and grid interface; diagnostics, monitoring, and software-enabled control; installation, testing, and quality assurance; and maintenance, troubleshooting, and safety culture. These findings allow for the determination of the skills that should be incorporated into graduate and technician degree programmes.

Table 3. Electric vehicle competency clusters derived from the review

Cluster	Illustrative capabilities	Representative studies
Vehicle systems and systems integration	Understand interaction among powertrain, electrical, mechanical, and control subsystems.	Tie & Tan (2013); Mwasilu et al. (2014); Sovacool et al. (2018)
Battery systems competence	Understand cells, modules, packs, SoC/SoH, thermal management, and BMS.	Lu et al. (2013); Hannan et al. (2017); Xiong et al. (2018); Zhang et al. (2022)
Charging infrastructure and grid interface	Design, install, plan, and troubleshoot charging systems and standards.	Yilmaz & Krein (2013); Habib et al. (2015); Knezovic et al. (2017); Micari et al. (2017); Mastoi et al. (2022); Wang et al. (2022)
Diagnostics, monitoring, and software-enabled control	Use diagnostic software, interpret data, monitor faults, and support predictive maintenance.	Das et al. (2020); Xiong et al. (2018); Fachrizal et al. (2020)
Installation, testing, and quality assurance	Commission equipment, conduct tests, document performance, and support quality control.	Martinez-Laserna et al. (2018); Liu et al. (2021); Wu et al. (2024)
Maintenance, troubleshooting, and safety culture	Perform safe servicing, fault isolation, and standards-based maintenance.	Deng (2015); Das et al. (2020); Zhang et al. (2022); Kumar & Alok (2020)

6.3 Cross-Cutting Workforce Competencies

Comparison of the two evidence streams revealed six different competencies that exist within each of the roles: systems thinking, digital fluency, communication, problem solving under uncertainty, responsibility, and lifelong learning. Figure 4 shows the common competency structure connecting the two domains. Table 4 supplements the figure by distinguishing how the same shared competency appears in data science and in EV work.

Figure 4. Cross-Cutting Competencies Connecting Data Science and Electric Vehicle Fields.

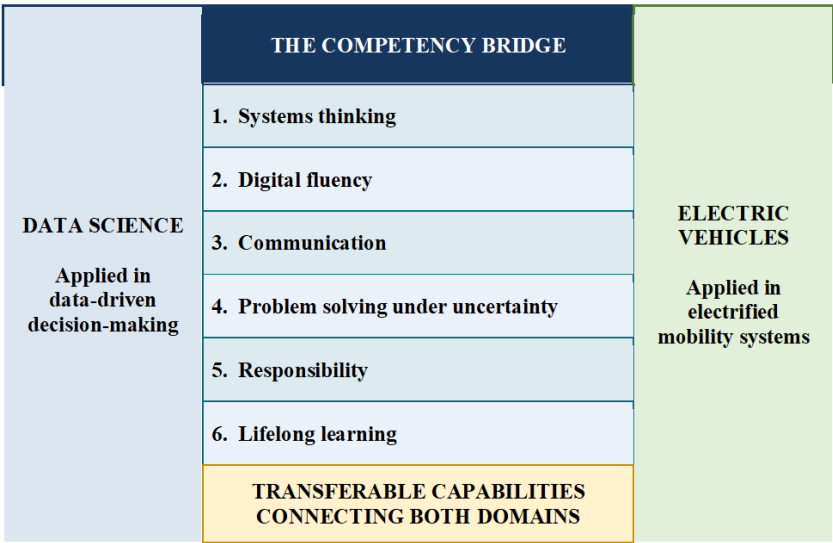


Table 4. Cross-cutting competencies shared by both fields

Cross-cutting competency	How it appears in data science	How it appears in EV work
Systems thinking	Links data, models, business processes, and decisions.	Links batteries, power electronics, software, charging, and safety systems.
Digital fluency	Programming, data handling, visualisation, and platform awareness.	Diagnostic software, telematics, monitoring systems, and smart charging.
Communication	Explain findings, uncertainty, and model implications.	Explain faults, safety issues, and operational guidance to users and teams.
Problem solving under uncertainty	Handle incomplete data, model limitations, and trade-offs.	Handle intermittent faults, charging variability, and hardware-software interactions.

Responsibility	Privacy, fairness, reproducibility, accountability.	Safety, standards compliance, energy reliability, environmental awareness.
Lifelong learning	Adapt to new methods, tools, and governance expectations.	Adapt to new chemistries, standards, charging technologies, and procedures.

To make the cross-domain comparison explicit, Table 5 groups the findings into broader competency categories and maps their manifestations across data science and EV work. The table shows that the two sectors differ in technical content but converge in systems reasoning, digital interpretation, professional communication, and responsible adaptation.

Table 5. Comparative mapping of competency categories across data science and electric vehicle industries

Competency category	Data science manifestation	Electric vehicle manifestation	Educational significance
Technical/domain-specific	Programming, data management, model development, software deployment	Battery systems, charging infrastructure, power electronics, diagnostics, high-voltage safety	Requires domain-specific courses, laboratories, tools, and supervised practice.
Analytical and digital	Statistical reasoning, model validation, data quality, interpretation, visualisation	Monitoring, fault interpretation, forecasting, charging analytics, location/capacity planning	Requires data interpretation, evidence-based decision-making, and systems-oriented problem solving.
Professional and communicative	Problem framing, stakeholder communication, teamwork, explanation of uncertainty	Multidisciplinary coordination, explanation of faults and safety issues, service communication	Supports project-based learning, teamwork, presentations, and communication with non-specialists.

Responsible and adaptive	Privacy, fairness, reproducibility, accountability, continuing learning	Safety, standards compliance, reliability, environmental responsibility, continuing learning	Requires explicit ethics/safety education, reflective judgement, standards awareness, and lifelong learning.
Systems and integration	Connecting data, models, organisational context, deployment, and decisions	Connecting battery, powertrain, software, charging, grid, and safety subsystems	Supports interdisciplinary curricula, capstone projects, and work-integrated learning.

6.4 Higher Education–Industry Alignment Mechanisms

The analysis of curriculum, training, employability, and workforce-preparation statements across the 40 included studies identified four recurring mechanisms for alignment, as summarised in Table 6. The first is competency-based curriculum mapping, through which programme outcomes, course content, and assessment are linked to the domain-specific and cross-cutting competencies identified in Sections 6.1–6.3. The second is authentic and work-integrated learning, which provides opportunities to apply knowledge to realistic datasets, laboratories, diagnostic tasks, software environments, multidisciplinary projects, and workplace problems. The third is recurring employer participation through advisory input, co-designed activities, internship partnerships, and periodic curriculum review. The fourth is flexible upskilling through modular, stackable, and continuing-learning pathways that allow graduates and incumbent workers to respond to changing technologies and standards. These mechanisms indicate that alignment is a continuing institutional process rather than a one-time curriculum redesign.

Table 6. Higher education–industry alignment mechanisms derived from the review

Alignment mechanism	Higher education application	Industry contribution
Competency-based curriculum mapping	Map identified competency clusters to programme outcomes, course content, assessment criteria, and graduate profiles.	Provide recurring feedback on changing occupational roles, competency requirements, and graduate performance.

Alignment mechanism	Higher education application	Industry contribution
Authentic and work-integrated learning	Use realistic projects, datasets, laboratories, diagnostic tasks, and multidisciplinary learning to develop applied judgement.	Support internships, workplace projects, practical exposure, mentoring, and industry-linked learning experiences.
Recurring employer participation	Embed advisory input, co-designed activities, periodic curriculum review, and structured feedback mechanisms.	Identify emerging skill needs, review curriculum relevance, and communicate changing workplace expectations.
Flexible upskilling pathways	Offer modular courses, micro credentials, and stackable learning opportunities for graduates and incumbent workers.	Signal new technologies and standards and contribute to continuing professional development and reskilling.

7. Discussion

7.1 To answer RQ1, six competency areas were identified as contributing to readiness for data science work: problem framing and stakeholder understanding; data acquisition, preparation, and quality management; analytical and modelling competence; communication and visualisation; coding, software, and deployment readiness; and ethical, collaborative, and adaptive capability. These competency areas relate to the knowledge of the various components of data science that are often discussed within both data science curricula and professional literature on the field (Crisan et al., 2021; De Veaux et al., 2017; Donoho, 2017; Hardin et al., 2015). Thus, the answer to this research question goes beyond competency with statistical techniques, programming languages, or machine learning techniques. Rather, competency in data science also requires understanding how to frame problems appropriately, perform analyses on data, communicate the findings of those analyses through effective visualisations, deploy analytical techniques as computer programmes, and to make responsible decisions about the problems that are solved by those data science techniques (Mehrabi et al., 2021; Saltz & Dewar, 2019).

The pattern of data science competence represented in Figure 2 and Table 2 indicates that the field is better understood as an end-to-end profession. While modelling skills are important, the value of such skills is contingent upon data quality, contextual understanding, reproducibility, communication, deployment, and ethical judgement. Each of these components has been recognised in the literature as essential components of data science education and practice (Hicks & Irizarry, 2018; Reinhart & Genovese, 2021). Thus, curricula that focus only upon the software component of data science may produce graduates who are technically capable of performing data

science tasks, but who may not be prepared to enter the workforce and effectively perform their duties.

7.2 With respect to RQ2, the six competency areas that emerged from the reviewed literature on EV workforce requirements were vehicle systems and systems integration; battery systems competence; charging infrastructure and grid interface; diagnostics, monitoring, and software-enabled control; installation, testing, and quality assurance; and maintenance, troubleshooting, and safety culture. These competency areas indicate that EV work requires competencies in electrical, electronic, software, infrastructure, diagnostic, and safety areas - all of which have been identified in various EV and infrastructure studies (Hannan et al., 2017; Lu et al., 2013; Xiong et al., 2018; Yilmaz & Krein, 2013). Figure 3 and the information summarised in Table 3 indicate that EVs are primarily a systems-centric technology. The systems included in EVs relate to, but are not limited to: batteries, battery charging, battery thermal management, battery diagnostics, power electronics, software systems, and safety systems (Das et al., 2020; Fachrizal et al., 2020; Mastoi et al., 2022; Zhang et al., 2022). Thus, competency requirements for EV technicians relate to the ability to diagnose these systems and perform various tasks on the EVs in a way that is safe throughout the life cycle of the EV.

7.3 The findings relevant to RQ3 reveal that there are six competencies that are present in both fields: systems thinking, digital fluency, communication, problem solving under uncertainty, responsibility, and lifelong learning. These competencies allow for individuals to work within the systems inherent to these fields. Furthermore, some of these competencies relate to the literature of both data science and EV fields. For instance, responsibility in relation to data science relates to concepts like data privacy, fairness, and reproducibility; however, responsibility in the field of EV relates to concepts like high-voltage safety, reliability of components, and environmental impact (Crisan et al., 2021; Ridgway, 2016; Sovacool et al., 2017). Figure 4 and Table 4 show that the shared competencies take domain-specific forms. The importance of responsible practices in the data science field is based upon the research regarding data ethics, privacy, bias, and fairness; however, studies within the field of EV indicate a focus on safety, interoperability, and reliability of the systems components (Das et al., 2020; Mehrabi et al., 2021; Saltz & Dewar, 2019). Digital fluency in the data science field relates to the use of programming and analytical software and platforms; however, digital fluency in the field of EV relates to concepts like diagnostic software, telematics systems, and smart charging systems. Although these competencies perform comparable functions in both fields, they should be developed through domain-specific curricula and learning activities. Thus, while the data science and EV curricula will include the technically-specific knowledge of each domain, each programme will utilise project-based learning to enable its students to develop these essential competencies. Furthermore, these components of project-based learning have also been recognised as valuable components of data science education and curricula itself (Baumer, 2015; Çetinkaya-

Rundel & Ellison, 2021; Dogucu et al., 2025). This model for integrating the two domains of knowledge and recognising the value of each of these competency areas will form the basis of the model for workforce competency convergence for individuals within these fields, as presented in Section 8.

7.4 In response to RQ4, Table 6 shows that higher education curricula and training systems can be aligned with workforce competency requirements in data science and the electric vehicle industry through four complementary mechanisms: competency-based curriculum mapping, authentic and work-integrated learning, recurring employer participation and flexible upskilling pathways. Competency-based curriculum mapping requires institutions to translate workforce requirements into programme learning outcomes, course content, learning activities and assessment criteria. In data science, this involves integrating statistics, computing, data management, communication and responsible practice rather than treating them as separate areas of knowledge (De Veaux et al., 2017; Hardin et al., 2015).

The second mechanism is authentic and work-integrated learning. Students require opportunities to apply knowledge through realistic datasets, software environments, laboratories, diagnostic tools, multidisciplinary projects and industry-based problems. Project-based learning can allow for integration between technical skills and problem identification, collaboration, communication and professional judgement. Integrative learning is especially relevant in an effort to address workplace preparedness, which requires the ability to integrate knowledge throughout the full spectrum of the profession rather than just the successful application of discrete skills or knowledge domains (Baumer, 2015; Çetinkaya-Rundel & Ellison, 2021; Hicks & Irizarry, 2018).

Third, recurring employer participation can help institutions monitor changes in occupational requirements and periodically update curricula. Employers can contribute through advisory committees, curriculum reviews, internships, mentoring, co-designed projects and feedback on graduate performance. Evidence connecting university course offerings with labour-market skills demonstrates the value of systematically mapping educational provision against changing workforce expectations (Javadian Sabet et al., 2024). However, curriculum alignment should not be reduced to short-term employer demands. Higher education must continue to develop foundational knowledge, critical inquiry, ethical reasoning and adaptable graduate capabilities (Tomlinson, 2012, 2017).

Fourth, flexible upskilling pathways—including modular courses, microcredentials, stackable qualifications and continuing professional development—can support both students and incumbent workers as technologies and standards evolve. Institutionally, these mechanisms require sustained collaboration among universities, employers and public agencies, consistent with the Triple Helix perspective on university–industry–government interaction (Etzkowitz & Leydesdorff, 2000). Their implementation must also remain sensitive to national

differences in infrastructure, regulation and institutional capacity. For example, German charging-station planning illustrates how local infrastructure and service requirements can shape EV-related competency priorities (Liu et al., 2021).

International evidence also indicates that alignment priorities must be adapted to national and sectoral contexts. German motorway-charging research foregrounds infrastructure planning and service-location requirements (Liu et al., 2021), whereas broader EV reviews emphasise standards, grid integration, charging policy, and coordinated infrastructure investment (Das et al., 2020; Mastoi et al., 2022). In the United States, data science curriculum guidance places stronger emphasis on integrating statistics, computing, data management, communication, ethics, and reproducible practice (De Veaux et al., 2017; Hardin et al., 2015). These differences suggest that the proposed alignment mechanisms are internationally relevant but should be implemented in accordance with local regulation, infrastructure, labour-market structure, and institutional capacity.

8. Proposed Higher Education–Industry Workforce Competency Alignment Framework

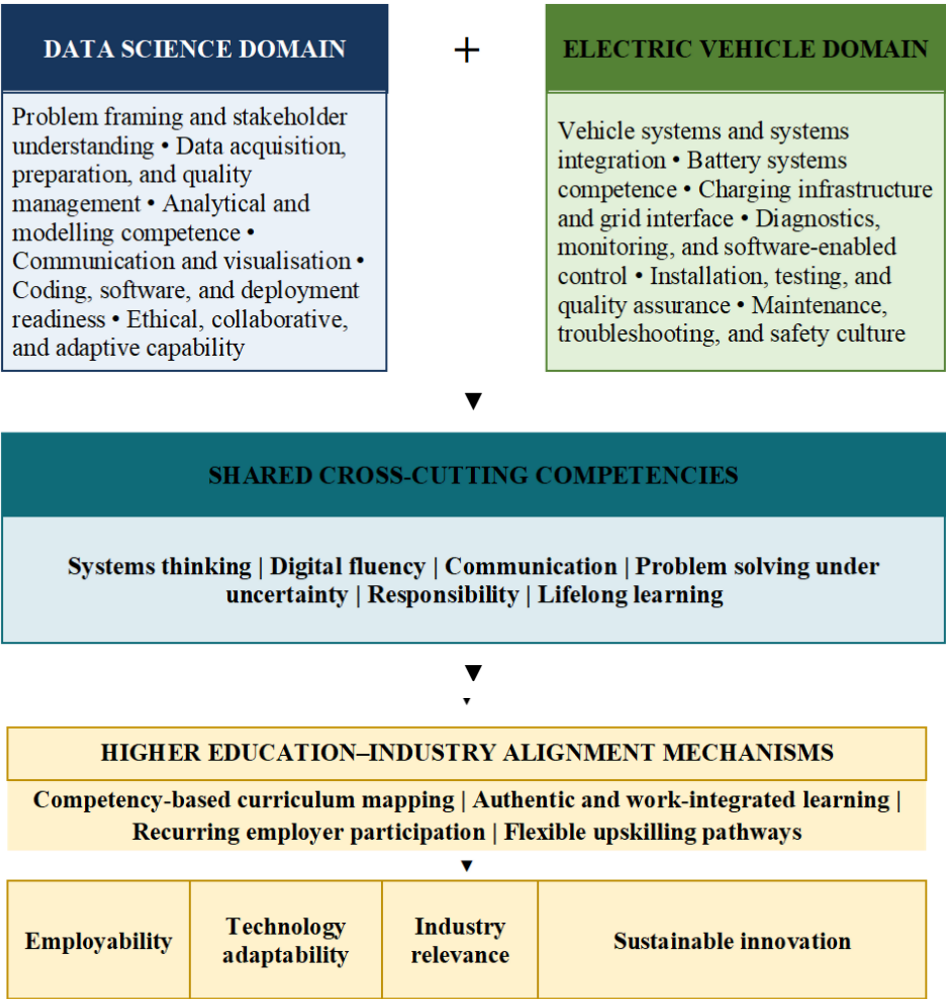
Based on the findings and the answers to RQ1–RQ4, this study proposes a higher education–industry competency alignment framework. The framework links domain-specific competencies in data science and EV work to shared cross-cutting capabilities and to the institutional mechanisms through which curricula can support workforce readiness. Its purpose is not to merge the two technical fields, but to show how higher education can translate distinct occupational requirements into comparable curriculum, pedagogy, and employability strategies.

The first domain within the model is the data science domain. This domain encompasses competencies in each of the following areas: problem framing and stakeholder understanding; data acquisition, preparation, and quality management; analytical and modelling competence; communication and visualisation; coding, software, and deployment readiness; and ethical, collaborative, and adaptive capability. Each of these competencies relates to the data science and data-driven knowledge that is required for positions in analytics, artificial intelligence, machine learning, business intelligence, and decision-making.

The second domain is the electric vehicle domain. This domain includes vehicle systems and systems integration; battery systems competence; charging infrastructure and grid interface; diagnostics, monitoring, and software-enabled control; installation, testing, and quality assurance; and maintenance, troubleshooting, and safety culture. This domain encompasses the knowledge required to develop and manufacture electric vehicles, their battery systems, charging infrastructure, and to provide vehicle diagnostics, maintenance, and mobility services.

Figure 5 presents the competency alignment framework. Data science and EV competencies remain domain specific, but both are connected through systems thinking, digital fluency, communication, problem solving under uncertainty, responsibility, and lifelong learning. These capabilities are translated into workforce readiness through four higher education–industry alignment mechanisms: competency-based curriculum mapping, authentic and work-integrated learning, recurring employer participation, and flexible upskilling pathways. The last stage in the framework includes the anticipated benefits of this convergence. These are sustainable innovation, industry relevance, technological adaptability and employability.

Figure 5. Higher Education–Industry Competency Alignment Framework for Data Science and Electric Vehicle Sectors.



9. Implications for Education, Policy, and Workforce Development

9.1 Implications for Higher Education Institutions

For higher education institutions, the results of this study indicate a shift from focusing on the coverage of the content within the discipline to focusing on the integration of the competencies within the curriculum for both data science and EV degrees. Within data science programmes, courses can integrate content related to statistics, programming, data management, data communication, data ethics, and an understanding of the problems that frame an organisation's requirements for data scientists. For EV programmes, courses can integrate content related to electrical engineering, mechanical engineering, battery systems, EV charging infrastructure, software systems, industry and safety standards, high-voltage systems, and EV sustainability.

These competency clusters can also be used to revise the graduate profiles and programme learning outcomes of the programmes. Instead of focusing upon the knowledge that will be required of the graduates, the outcomes can focus upon the set of competencies and capabilities of the graduates, such as their ability to work with real data and equipment, to work within ill-structured problems, and to make important decisions. Accordingly, assessment of the students can shift towards using problems and projects that are relevant to the industry, rather than focusing upon examinations of the students' knowledge of the topics.

9.2 Implications for Technical and Vocational Education and Training Providers

For technical and vocational education and training providers, the findings indicate the possibility of creating modular and stackable programmes. Courses that can be targeted at newcomers may include high-voltage safety, diagnostics, data literacy, charging systems. Courses that can be targeted at more advanced students may include systems engineering, machine learning, smart charging and battery analytics. These short courses can be used as part of a broader qualification and enable TVET to cater to students of varying levels of experience and professional goals.

9.3 Implications for Employers

The framework can also be applied to the domain of work. Employers can specify the required competences for a given position in a job specification and also specify the technical competences that can be gained by an employee after employment in a particular organisation.

9.4 Implications for Policymakers and Education Administrators

Administrators and policymakers can enhance convergence through flexible micro-credentials, work-integrated learning, staff development, common industry-university research labs, interdisciplinary studies and industry involvement. Quality assurance and accreditation can ensure that curricula can be updated with minimal delay whilst continuing to uphold ethical standards, safety and academic quality.

9.5 Implications for Researchers

For researchers, this study provides a basis for testing the proposed model through various methods such as expert panels, curriculum mapping, graduate and employer surveys, assessments of the students who completed the programmes, and research into the employment rates of these graduates. Additionally, it may also be beneficial for future researchers to perform comparative studies of the competencies within various countries, institutions, and levels of education and employment.

10. Limitations and Future Research Directions

This systematic literature review has several limitations. First, the multidisciplinary literature uses varied terminology, so some relevant studies may not have been captured despite the systematic search strategy. Second, a portion of the EV evidence consisted of technical reviews, systems studies, and infrastructure-planning research from which workforce competency requirements had to be inferred; not all included EV studies directly examined workers, employers, or educational programmes. The findings should therefore be interpreted as a structured synthesis of explicit and technically inferred competency requirements rather than a direct measurement of employer demand or graduate competency levels. Third, the synthesis is qualitative and thematic rather than statistical, so it identifies patterns of emphasis rather than effect sizes or causal relationships. Fourth, only English-language peer-reviewed journal publications were included; conference papers, reports, non-reviewed publications, and non-English studies were excluded from the 40-study corpus. Fifth, the review did not systematically stratify findings by country, student socioeconomic background, institution type, or access to work-integrated learning. Consequently, the discussion of equity and international transferability is theoretically informed but should not be interpreted as an empirical test of inequality across the included studies.

The proposed higher education–industry competency alignment framework and the four higher education–industry alignment mechanisms were derived from thematic synthesis rather than direct empirical testing. Future research can examine the applicability of these models through the collection of data from experts in the field, graduates of EV programmes, surveys of industry employees, programme assessments, and investigations into the workforce data of EV industries. It would also be beneficial to investigate how competencies in data science and EV-related fields correspond to specific occupations within their respective industries. Finally, conducting studies that compare the competency models of different countries and industries will help to determine whether the models are universally applicable or only applicable in specific contexts.

11. Conclusion

This systematic literature review synthesised 40 peer-reviewed journal studies to examine workforce competency requirements and higher education–industry

alignment in data science and the electric vehicle industry. Data science requires capabilities in problem framing and stakeholder understanding; data acquisition, preparation, and quality management; analytical and modelling competence; communication and visualisation; coding, software, and deployment readiness; and ethical, collaborative, and adaptive capability. EV work requires capabilities in vehicle systems and systems integration; battery systems competence; charging infrastructure and grid interface; diagnostics, monitoring, and software-enabled control; installation, testing, and quality assurance; and maintenance, troubleshooting, and safety culture. Across both sectors, the review identified six transferable capabilities and four institutional alignment mechanisms with direct relevance to curriculum development, graduate employability, and workforce preparation.

The broader conclusion is that the higher education–industry gap cannot be addressed by adding technical content alone. Alignment requires competency-based curriculum mapping, authentic and work-integrated learning, recurring employer participation, flexible upskilling pathways, and policy arrangements that support timely but educationally responsible curriculum renewal. The proposed higher education–industry competency alignment framework shows how distinct high-tech domains can be connected through shared capabilities and institutional mechanisms, offering a basis for policy and curricular responses to changing labour-market demands in the new economy.

References

- [1] Baumer, B. (2015). A data science course for undergraduates: Thinking with data. *The American Statistician*, 69(4), 334–342. <https://doi.org/10.1080/00031305.2015.1081105>
- [2] Blei, D. M., & Smyth, P. (2017). Science and data science. *Proceedings of the National Academy of Sciences*, 114(33), 8689–8692. <https://doi.org/10.1073/pnas.1702076114>
- [3] Cao, L. (2017). Data science: A comprehensive overview. *ACM Computing Surveys*, 50(3), Article 43, 1–42. <https://doi.org/10.1145/3076253>
- [4] Çetinkaya-Rundel, M., & Ellison, V. (2021). A fresh look at introductory data science. *Journal of Statistics and Data Science Education*, 29(sup1), S16–S26. <https://doi.org/10.1080/10691898.2020.1804497>
- [5] Crisan, A., Fiore-Gartland, B., & Tory, M. (2021). Passing the data baton: A retrospective analysis on data science work and workers. *IEEE Transactions on Visualization and Computer Graphics*, 27(2), 1860–1870. <https://doi.org/10.1109/TVCG.2020.3030340>
- [6] Das, H. S., Rahman, M. M., Li, S., & Tan, C. W. (2020). Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review. *Renewable and Sustainable Energy Reviews*, 120, 109618. <https://doi.org/10.1016/j.rser.2019.109618>

- [7] De Veaux, R. D., Agarwal, M., Averett, M., Baumer, B. S., Bray, A., Bressoud, T. C., Bryant, L., Cheng, L. Z., Francis, A., Gould, R., Kim, A. Y., Kretchmar, M., Lu, Q., Moskol, A., Nolan, D., Pelayo, R., Raleigh, S., Sethi, R. J., Sondjaja, M., ... Ye, P. (2017). Curriculum guidelines for undergraduate programs in data science. *Annual Review of Statistics and Its Application*, 4, 15–30.
<https://doi.org/10.1146/annurev-statistics-060116-053930>
- [8] Deng, D. (2015). Li-ion batteries: Basics, progress, and challenges. *Energy Science & Engineering*, 3(5), 385–418. <https://doi.org/10.1002/ese3.95>
- [9] Dhar, V. (2013). Data science and prediction. *Communications of the ACM*, 56(12), 64–73. <https://doi.org/10.1145/2500499>
- [10] Dogucu, M., Demirci, S., Bendekgey, H., Ricci, F. Z., & Medina, C. M. (2025). A systematic literature review of undergraduate data science education research. *Journal of Statistics and Data Science Education*, 33(4), 459–471.
<https://doi.org/10.1080/26939169.2025.2486656>
- [11] Donoho, D. (2017). 50 years of data science. *Journal of Computational and Graphical Statistics*, 26(4), 745–766.
<https://doi.org/10.1080/10618600.2017.1384734>
- [12] Etzkowitz, H., & Leydesdorff, L. (2000). The dynamics of innovation: From national systems and “Mode 2” to a triple helix of university-industry-government relations. *Research Policy*, 29(2), 109–123.
[https://doi.org/10.1016/S0048-7333\(99\)00055-4](https://doi.org/10.1016/S0048-7333(99)00055-4)
- [13] Fachrizal, R., Shepero, M., van der Meer, D., Munkhammar, J., & Widén, J. (2020). Smart charging of electric vehicles considering photovoltaic power production and electricity consumption: A review. *eTransportation*, 4, 100056. <https://doi.org/10.1016/j.etrans.2020.100056>
- [14] Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Pedreschi, D., & Giannotti, F. (2018). A survey of methods for explaining black box models. *ACM Computing Surveys*, 51(5), Article 93, 1–42.
<https://doi.org/10.1145/3236009>
- [15] Habib, S., Kamran, M., & Rashid, U. (2015). Impact analysis of vehicle-to-grid technology and charging strategies of electric vehicles on distribution networks: A review. *Journal of Power Sources*, 277, 205–214.
<https://doi.org/10.1016/j.jpowsour.2014.12.020>
- [16] Hannan, M. A., Lipu, M. S. H., Hussain, A., & Mohamed, A. (2017). A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations. *Renewable and Sustainable Energy Reviews*, 78, 834–854.
<https://doi.org/10.1016/j.rser.2017.05.001>
- [17] Hardin, J., Hoerl, R., Horton, N. J., Nolan, D., Baumer, B., Hall-Holt, O., Murrell, P., Peng, R., Roback, P., Temple Lang, D., & Ward, M. D. (2015). Data science in statistics curricula: Preparing students to think with data. *The American Statistician*, 69(4), 343–353.
<https://doi.org/10.1080/00031305.2015.1077729>

- [18] Hicks, S. C., & Irizarry, R. A. (2018). A guide to teaching data science. *The American Statistician*, 72(4), 382–391.
<https://doi.org/10.1080/00031305.2017.1356747>
- [19] Javadian Sabet, A., Bana, S. H., Yu, R., & Frank, M. R. (2024). Course-Skill Atlas: A national longitudinal dataset of skills taught in U.S. higher education curricula. *Scientific Data*, 11, 1086. <https://doi.org/10.1038/s41597-024-03931-8>
- [20] Knezovic, K., Marinelli, M., Zecchino, A., Andersen, P. B., & Traeholt, C. (2017). Supporting involvement of electric vehicles in distribution grids: Lowering the barriers for a proactive integration. *Energy*, 134, 458–468.
<https://doi.org/10.1016/j.energy.2017.06.075>
- [21] Kumar, R. R., & Alok, K. (2020). Adoption of electric vehicle: A literature review and prospects for sustainability. *Journal of Cleaner Production*, 253, 119911. <https://doi.org/10.1016/j.jclepro.2019.119911>
- [22] Liu, J., Peper, J., Lin, G., Zhou, Y., Awasthi, S., Li, Y., & Rehtanz, C. (2021). A planning strategy considering multiple factors for electric vehicle charging stations along German motorways. *International Journal of Electrical Power & Energy Systems*, 124, 106379.
<https://doi.org/10.1016/j.ijepes.2020.106379>
- [23] Lu, L., Han, X., Li, J., Hua, J., & Ouyang, M. (2013). A review on the key issues for lithium-ion battery management in electric vehicles. *Journal of Power Sources*, 226, 272–288. <https://doi.org/10.1016/j.jpowsour.2012.10.060>
- [24] Martinez-Laserna, E., Sarasketa-Zabala, E., Villarreal, I., Stroe, D.-I., Swierczynski, M., Warnecke, A., Timmermans, J.-M., Goutam, S., Omar, N., & Rodriguez, P. (2018). Technical viability of battery second life: A study from the ageing perspective. *IEEE Transactions on Industry Applications*, 54(3), 2703–2713. <https://doi.org/10.1109/TIA.2018.2801262>
- [25] Mastoi, M. S., Zhuang, S., Munir, H. M., Haris, M., Hassan, M., Usman, M., Bukhari, S. S. H., & Ro, J.-S. (2022). An in-depth analysis of electric vehicle charging station infrastructure, policy implications, and future trends. *Energy Reports*, 8, 11504–11529.
<https://doi.org/10.1016/j.egyr.2022.09.011>
- [26] Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. *ACM Computing Surveys*, 54(6), 1–35. <https://doi.org/10.1145/3457607>
- [27] Micari, S., Polimeni, A., Napoli, G., Andaloro, L., & Antonucci, V. (2017). Electric vehicle charging infrastructure planning in a road network. *Renewable and Sustainable Energy Reviews*, 80, 98–108.
<https://doi.org/10.1016/j.rser.2017.05.022>
- [28] Mwasilu, F., Justo, J. J., Kim, E.-K., Do, T. D., & Jung, J.-W. (2014). Electric vehicles and smart grid interaction: A review on vehicle-to-grid and renewable energy sources integration. *Renewable and Sustainable Energy Reviews*, 34, 501–516. <https://doi.org/10.1016/j.rser.2014.03.031>

- [29] Nolan, D., & Temple Lang, D. (2010). Computing in the statistics curriculum. *The American Statistician*, 64(2), 97–107.
<https://doi.org/10.1198/tast.2010.09132>
- [30] Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372, n71. <https://doi.org/10.1136/bmj.n71>
- [31] Provost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making. *Big Data*, 1(1), 51–59.
<https://doi.org/10.1089/big.2013.1508>
- [32] Reinhart, A., & Genovese, C. R. (2021). Expanding the scope of statistical computing: Training statisticians to be software engineers. *Journal of Statistics and Data Science Education*, 29(sup1), S20–S29.
<https://doi.org/10.1080/10691898.2020.1845109>
- [33] Ridgway, J. (2016). Implications of the data revolution for statistics education. *International Statistical Review*, 84(3), 528–549.
<https://doi.org/10.1111/insr.12110>
- [34] Saltz, J. S., & Dewar, N. (2019). Data science ethical considerations: A systematic literature review and proposed project framework. *Ethics and Information Technology*, 21, 197–208. <https://doi.org/10.1007/s10676-019-09502-5>
- [35] Sovacool, B. K., Axsen, J., & Kempton, W. (2017). The future promise of vehicle-to-grid (V2G) integration: A sociotechnical review and research agenda. *Annual Review of Environment and Resources*, 42, 377–406.
<https://doi.org/10.1146/annurev-environ-030117-020220>
- [36] Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. *BMC Medical Research Methodology*, 8, 45. <https://doi.org/10.1186/1471-2288-8-45>
- [37] Tie, S. F., & Tan, C. W. (2013). A review of energy sources and energy management system in electric vehicles. *Renewable and Sustainable Energy Reviews*, 20, 82–102. <https://doi.org/10.1016/j.rser.2012.11.077>
- [38] Tomlinson, M. (2012). Graduate employability: A review of conceptual and empirical themes. *Higher Education Policy*, 25(4), 407–431.
<https://doi.org/10.1057/hep.2011.26>
- [39] Tomlinson, M. (2017). Forms of graduate capital and their relationship to graduate employability. *Education + Training*, 59(4), 338–352.
<https://doi.org/10.1108/ET-05-2016-0090>
- [40] Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. *Journal of Business Logistics*, 34(2), 77–84.
<https://doi.org/10.1111/jbl.12010>

- [41] Wang, L., Yang, C., Zhang, Y., & Bu, F. (2022). Research on multi-objective planning of electric vehicle charging stations considering the condition of urban traffic network. *Energy Reports*, 8, 11825–11839.
<https://doi.org/10.1016/j.egy.2022.08.242>
- [42] Wu, C., Wang, Y., Shi, Q., & Gao, S. (2024). A two-layer planning method for location and capacity determination of public electric vehicle charging stations. *International Journal of Electrical Power & Energy Systems*, 161, 110205. <https://doi.org/10.1016/j.ijepes.2024.110205>
- [43] Xiong, R., Li, L., & Tian, J. (2018). Towards a smarter battery management system: A critical review on battery state of health monitoring methods. *Journal of Power Sources*, 405, 18–29.
<https://doi.org/10.1016/j.jpowsour.2018.10.019>
- [44] Yilmaz, M., & Krein, P. T. (2013). Review of charging power levels and infrastructure for plug-in electric and hybrid vehicles. *Proceedings of the IEEE*, 101(1), 215–228. <https://doi.org/10.1109/JPROC.2012.2212912>
- [45] Zhang, X., Li, Z., Luo, L., Fan, Y., & Du, Z. (2022). A review on thermal management of lithium-ion batteries for electric vehicles. *Energy*, 238, 121652. <https://doi.org/10.1016/j.energy.2021.121652>