

Article

Construction Education Alignment with Industry Skills Demands: A Data-Driven Evaluation Using Sampled Evidence in Australia

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Abstract

The Australian construction industry is currently navigating a productivity challenge in which workforce skills shortages represent a contributing factor. Historically, attempts to quantify this deficit have relied upon subjective surveys or ethically complex data collection methodologies, lacking the objective scale required for policy reform. To bridge this methodological gap and contribute to the literature with a current skills alignment analysis, this research introduces a natural language processing (utilising SBERT)-driven computational approach to explore the alignment between industry demand and educational supply. A sample of 3468 industry job advertisements from 2016 to 2018 and in 2026 were mapped against a weighted national educational supply vector (72.5% Vocational Education and Training, 27.5% Higher Education) using the standardised Australian Skills Classification taxonomy. The analysis indicates that curriculum–industry misalignment is a potential structural contributor to the skills gap in the sampled construction skills gap. Cosine similarity and Spearman’s rank analyses exposed a misalignment of skills priority by academia ($\rho_{\text{top20}} = 0.32$ and $\rho_{\text{global}} = 0.43$). While the education sector dedicates nearly 90% of its combined curriculum to specialist tasks skills, these skills showed a misalignment (60%) with rapidly shifting industry demands. Furthermore, while explicit demand for technology tools skills remained stagnant, a misalignment (54%) quantitatively reflects the documented industry concerns regarding digital readiness caused by a lag in digital-skills training. Ultimately, this study contributes a data-driven methodology and a current skills gap analysis that enables educational policymakers to conduct agile, computation-driven curriculum audits. This supports more frequent and evidence-informed curriculum review in response to the evolving Australian construction industry skill demands.

Keywords: construction industry; skills gap; curriculum alignment; natural language processing (NLP); labour market analytics; engineering education; job advertisements

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1. Introduction

1.1. Overview

The Australian construction industry, valued at circa \$50 billion, amounts to 7% of Australia's GDP [1]. This makes it the third largest industry sector in Australia [2]. The industry is currently facing severe productivity issues [3], driven by a notable skills shortage in labour [4–6]. The issue is further exacerbated as the Australian construction industry is predicted to have a labour shortage of 197,000 infrastructure workers across all occupational groups, including tradespeople, engineers and project managers [7]. Much of the construction sector workforce have also been found to be ageing. In the USA, over 20% of construction workers are aged 55 years and older, nearing retirement [6]. Similarly in Australia 40% of workers in project management, structures, civil trades and labour are over the age of 45 [8]. This may suggest that workforce turnover is imminent, and the construction industry must look for its next generation of skilled workers.

The emerging workforce is deficient in digital competences such as BIM and AI in construction and engineering and in important soft skills such as communication, creativity and team working [9,10]. A total of 81% of Australian businesses report that candidates lack appropriate skills and experience [7]. Many firms face high labour costs even though workers feel underpaid and are unable to invest in upskilling [11]. This makes it economically challenging to recruit better talent.

The ramifications of this are damaging, with declining productivity resulting in rising project costs. Along with persistent cost and time blowouts across the construction industry, profitability is declining, with average net profit margin of a mere 2.3% in 2024 [3,12]. The construction industry also faces quality issues, particularly prevalent in Class 2 residential apartment buildings in Sydney, Australia. The skills shortage, in combination with other factors, has impeded workplace productivity. Despite the growth the construction industry experienced, productivity gains within the sector have remained minimal, with multifactor productivity fluctuating: declining by 0.5% in 2021, rising marginally by 0.3% in 2022, declining again by 0.8% in 2023, and recovering to 2% in 2024 [13,14]. The growing skills concern has also hindered innovation and caused low adoption of transformative technologies, with 64% of construction businesses identifying lack of skilled workers as barriers to innovation [15].

To overcome these barriers, the existing literature suggests employing virtual design and construction engineering techniques [16] and embracing construction industry 4.0 principles. The literature consistently shows that promoting innovative and modern methods of construction is key in addressing these challenges [3,7]. However, to do this and build infrastructure sustainably, the industry needs to address gaps in skills [17]. Noting there is a demonstrated skills shortage, there is a clear call to invest in upskilling and multi-skilling initiatives [18,19], as well as in university and training curricula that are aligned with industry needs [20]. For example, BIM is often introduced only at an introductory level, with limited progression to advanced applications such as scheduling, cost estimation, clash detection and site planning, despite these being standard in industry practice. In many programs, BIM content is fragmented across isolated courses rather than embedded [20].

1.2. Problem Statement

The skills shortage in the Australian construction industry is a multi-faceted issue documented across various domains. Master Builders Australia [21] highlights the immediate volumetric shortfall in the trades sector, calling for a 10% annual workforce growth. From a demographic perspective, Francis and Paton-Cole [22] project long-term workforce deficits driven by an aging population, particularly in Victoria. Furthermore, Ding

et al. [11] quantified the direct operational consequences of these shortages, demonstrating their negative impact on construction supply chain performance.

Previous empirical studies identifying skill shortages, analysed in Section 2, have provided valuable foundational evidence. However, they frequently rely on localised surveys or interviews rather than extracting high-volume, objective demand signals directly from job advertisements. While this critically verifies the skills gap, there remains a degree of subjectivity and bias that is present because of this methodology. The literature also repeatedly posted the need for a high frequency skills gap analysis likely dictated by the turnover rate and the rapidly evolving nature of the construction industry [23–25]. There is a clear need for an objective skills gap analysis removing the element of bias and embracing the rapidly evolving Australian construction landscape.

1.3. Objectives

The aim of this paper is to explore how do the currently demanded skills in the Australian construction industry, derived from labour market data, differ from the skills currently covered by established industry training curricula, thereby determining the skills gap and priority skill areas for intervention. To successfully answer this research question, the objectives of this study are to: (1) quantitatively establish the skills-demand profile of Australian construction job advertisements; (2) establish the coverage of skills within official VET data and accreditation frameworks; (3) quantify the disparity between the required skill demands (Objective 1) and the skill supply (Objective 2); (4) identify which skill mismatches are priority targets for intervention.

In this study, labour productivity is defined as the efficiency with which workforce inputs are transformed into construction outputs by deploying human skill [23,24]. Workforce skills are framed as strategic intangible assets within Human Capital Theory [26] and the Resource-Based View [27]. Misalignment between demanded and supplied skills constrains productivity. While artificial intelligence is reshaping job roles within construction, this study treats AI as an analytical instrument. The intention here is to enable higher-frequency, objective skill requirements.

Pedagogically, this study contributes an evidence-based curriculum alignment mechanism grounded in constructive alignment theory [28]. In a constructively aligned curriculum, the Intended Learning Outcomes (ILOs) correspond to the required graduate capabilities. In this study's methodology, the formal educational supply vectors (VET competencies and HE accreditation standards) act as the documented ILOs (objective 2), while the industry job advertisements serve as the target capabilities (objective 1). By mathematically measuring the divergence between these two vectors (objectives 3 and 4), this enables educators to evaluate whether intended learning outcomes (supply) correspond to externally validated skill demands through job ads.

2. Literature Review

2.1. Industry Context and Skills Shortage Epidemic

2.1.1. The Industry Context: A Macro-Level Overview

The Australian construction industry is vast. Its impact far exceeds its tangible deliverables. For instance, a residential project becomes a placemaking project, while transmission line projects become vital for energy distribution between Australian states [29]. The sector supports the livelihoods of nearly one in 11 Australians, who are employed directly or indirectly in the construction sector as of May 2024 [21]. This shows how the impact far exceeds contribution to infrastructure alone. The Master Builders Australia [21] future outlook report analysed Australian Bureau of Statistics (ABS) data and found that the industry loses circa 8% of the workforce every year due to natural causes. To recover from

these losses and to ensure sustainable growth of the construction industry to support the infrastructure boom in Australia, the workforce needs a 10% annual growth [21]. In 2024, there was a net positive labour growth within the sector, with an additional 50,000 workers entering the workforce compared to those leaving. Worryingly, however, those new to the industry are far less skilled than those departing. This causes a workforce shortage of skilled workforce, with the Master Builders Australia [21] future outlook report calling for better industry, government, and academia collaboration to alleviate this gap.

Francis and Paton-Cole [22] identified how Victoria will need to double its construction workforce by 2046; however the number of workers and their skill levels are declining, highlighting a legitimate concern. Traditionally, training and upskilling has been left to the employees who seek training through vocational education training (VET) or higher education (HE) to ensure they are well prepared to work in the industry. With the growing skills shortage, declining multifactor labour productivity rates and profitability, the Master Builders Australia [21] future outlook report calls for intervention and for the industry to invest in meaningful continuous professional development (CPD). The report also identified that only 13.6% of the workforce was comprised of women as of May 2024 [21], positing that this labour group is untapped within the market and could help with the skills shortage. However, this is only possible if there is a robust training system to support this. Further, the report largely relied on the ABS data, with limited peer-reviewed journals cited. Whilst it is industry relevant, it lacks the academic rigour of a white paper.

2.1.2. Factors Affecting Labour Productivity

Labour productivity in the construction sector refers to the number of actual labour units required to complete a task relative to the average number of labour units normally required [24]. The decline in labour productivity in the Australian construction sector has been a growing yet unsurprising trend. Hasan et al. [24] conducted a systematic review of factors contributing to construction labour productivity. A total of 46 articles were filtered for further analysis through a survey of the literature conducted over the period from 1986 to 2016. Most of these articles, 25 out of the 46, found that skills shortage is a key cause of low productivity. The review extended to the global context, with the findings at large showing that CPD was a major focus, as productivity is a measure of efficiency through continuous improvement. The implications of emerging technology such as AI for aiding CPD and addressing productivity issues were understudied during the 3 decades covered by this review. Adebawale and Agumba [23] also conducted an analysis of construction labour productivity. Of the 460 global articles that were analysed, Australia had the highest number of articles surrounding labour productivity, showcasing the local presence of this issue. The study found that some of the key factors that contribute to low productivity are skills shortage, which is in agreement with Hasan et al. [24]. Absenteeism, low worker motivation, rework arising from incompetence and physical fatigue were also found to be other factors contributing to low productivity. Trivially, it was also found that small changes to productivity can yield considerable increase in profitability by reducing costs. Hence, the industry absolutely benefits from increasing the workforce productivity, despite much of the effort to tackle this currently being spearheaded by academia. Both Adebawale and Agumba [23] and Hasan et al. [24] independently concluded that future research must explore the impact of emerging technologies, such as AI, on construction productivity.

Nasirzadeh et al. [25] set out to identify the most significant factors affecting labour productivity in Australian construction. The white paper's methodology utilised a literature review to identify key factors, which were then substantiated by eight interviews. The factors were subsequently ranked and prioritised using the Decision Making Trial and Evaluation Laboratory (DEMATEL) method. Through the DEMATEL method, the

study found the five most significant factors affecting labour productivity in Australian multi-storey building projects to be once again the level of skill and experience, fatigue, inadequate supervision, award rates and communication problems with foreign workers. The DEMATEL method was a robust methodology used to prioritise the factors. DEMATEL [30], originally developed by the Battelle Memorial Association in Geneva, is an effective method for analysing causal relationships within a system. The skills issue and communication issues coincide with the findings of Adebawale and Agumba [23] and Hasan et al. [24]. The scope of this study, however, was limited in nature, as only 10 journal articles were analysed to obtain an initial list of factors. This is insufficient to draw a generalised finding. The study was also limited to multi-storey building construction projects in Victoria, Australia; therefore, it does not account for projects in other Australian states or infrastructure projects, making its findings rather localised.

Huynh et al. [31], through a combination of literature review, expert interviews, and on-site observations, identified resource utilisation, particularly workforce experience and training level, as a key factors influencing construction productivity. The study developed a practical framework where the insufficient experience of workers and a lack of ongoing training were all cited as recurring causes of low site performance. Supporting these findings, Elbashbishy and El-adaway [32] employed both expert-based surveys and advanced machine learning techniques to evaluate the impact of various inefficiencies across construction trades in the US. Their results reinforce the finding that a lack of skill and experience among workers and foremen is one of the most severe and consistently reported contributors to productivity losses across multiple trades. Collectively, these studies underscore the urgent need for targeted upskilling and experience-based workforce development initiatives to address productivity shortfalls in construction.

The skills shortage is a recurring theme amongst various articles, as a key cause of the low productivity issue. Jobs and Skills Australia [33] provides a list of occupations where employers are unable to or find it difficult to fill vacancies. The Australian construction industry has been at the top of the list since 2022, with an acute skills shortage of 65–75%. The difficulty employers face in filling roles is often a mix of factors, not just a shortage of skilled applicants. These can include wages, working conditions, and job requirements. While low pay is a key factor, employers rarely adjust wages, a trend that showed only about a 1% increase [33]. This minimal wage growth, a consistent trend from 2012 to 2024, has become the industry norm. Because employers have been so reluctant to adjust pay to attract talent, a disproportionate amount of pressure is placed on the skill requirements for a role. This highlights the need for a greater focus on skills, as it has become a primary driver of employment decisions for both job seekers and employers.

Accordingly, the productivity framing in this study should be read as contextual rather than deterministic. Skills shortages are repeatedly identified as one factor affecting construction productivity, but they interact with other labour-market and organisational factors. The contribution of this study is therefore to quantify one component of the productivity problem: the extent to which formal education and training provision align with observed employer skill demand.

2.1.3. Workforce Demographics and Retention Challenges

Egbelakin et al. [34] set out to address the skills gap epidemic in the construction workforce. The study confirmed that Australia has a major skills gap issue, drawing comparisons with the US, where a similar issue exists. The study applies a novel lens, by recommending that the industry work together with communities to engage young people and women in construction. Providing targeted training to minorities such as young people, women, migrants and refugees could alleviate the lack of skills in construction by tapping into these underutilised demographic groups [21,34]. However, this will not be

feasible without education and training, with the study being in agreement with the literature in general that there is a need for better training.

Baker et al. [35] extended this idea by investigating how we can address the skills shortage by tapping into the female demographic in the construction sector, substantiated by previous articles that had identified this as a good strategy. There has been a consistent underrepresentation of women in the Australian construction sector since the early 2000s. It was found that women who changed careers to work in the construction sector did so out of genuine interest and excitement for the field. This finding, while important, is somewhat self-evident, as such enthusiasm is likely necessary for any major career shift. This prompts a key question: how can the industry foster this sense of interest and excitement more broadly, while also equipping women with the confidence and competencies needed to overcome initial apprehension? Currently, the upskilling process demands substantial time and investment, which itself serves as a major barrier for women seeking to enter and thrive in construction roles. This, once again, highlights the need for not just training, but efficient upskilling to facilitate career transitions into the construction sector.

Alkilani et al. [36] investigated how refugees, asylum seekers and migrants find meaningful work in the Australian construction sector. Their survey of these demographics yielded 40 responses, of which the primary insight was how this group, contrary to popular belief, is highly capable and can help address the skills shortage. The survey responses indicated that some of these individuals even had a PhD, and most were of peak working age. The results found that women were generally better qualified than men. However in the construction industry, women are underrepresented for reasons mentioned previously, such as a skills shortage [21,34,35]. Hence addressing the skills shortage is a validated motivator for this research. Alkilani et al. [36] call for the important role educational institutions play to circumvent the barriers faced by this group. This validates the important role upskilling and training plays in this skills shortage epidemic. Overall, it was found that currently the construction industry does little to help this group.

Alkilani and Loosemore [37] further examined this in detail by investigating the challenges faced by skilled female migrants in the Australian construction industry. Through interviewing 16 skilled women migrants seeking employment, the article confirmed that there is virtually no support available from the government or the industry, to help female skilled migrants build the necessary intellectual, social and cultural capital to improve their employability in the construction labour market. One of the main factors that undermine female skilled migrant employability is education/qualifications (intellectual and cultural capital). The study found that even when these women take steps to improve their employability, such as obtaining new qualifications or adjusting their job expectations, they often remain dependent on informal networks to find opportunities. This suggests that closing the skills gaps within these minority groups may not completely solve the issue of employability. However, this is not surprising, as in many industries, prospective employees rely on connections and referrals to secure employment. Existing literature on underrepresented demographics in the Australian construction industry is well established. Current research posits that integrating migrants, refugees, women and young adults into the workforce offers a viable strategy to mitigate the sector's skills gap epidemic, provided that there is an efficient system to upskill and train these individuals for the local context.

2.1.4. Existing Training Paradigms and Resource Capabilities

The Resource Based View (RBV) theory posits that a firm's competitive advantage is driven by its tangible and intangible resources [27]. Workers' skills fall under the category of intangible resources. These are harder to replicate. Hence, developing workers' skills can lead to a competitive advantage as they are rare and valuable [27,38]. This is also why

employers place a large and valid emphasis on skills when hiring potential candidates. Bridging the skills gap requires not only technical training but also pedagogically aligned curricula where learning outcomes are directly mapped to employer needs. Ding et al. [11] investigated how skills shortage impacts the performance of the construction supply chain in Australia, through the lens of RBV. By employing a survey-based methodology, their 113 responses indicated that 45% of respondents find that employees within the construction sector lack training. A total of 56% agreed they had an unmatched skill set. This calls for urgent upskilling and training. The results had a Cronbach's alpha value of 0.925, showing a high level of reliability. Ding et al. [11] further conducted a regression analysis which substantiated the undeniable role skills shortage plays in project performance. A key reason for the skill shortage is that workers are underpaid and do not have sufficient income to further upskill themselves. The participants of the survey also found that a lack of employer-provided training is an issue that is affecting performance. The authors conclude that the skills shortage affects the future of the construction industry by reducing productivity.

McLaughlin [39] set out to identify techniques available to the Australian construction sector in minimising the effects of skilled labour shortage. This study involved interviewing 20 employees with over 25 years of experience at established contractors, which is a key strength. The participants called for investment in training and a system to develop capabilities such as a training platform within the industry. There is a clear need for companies to develop in-house training programs for career development and job satisfaction. Job satisfaction may be an important dimension of worker productivity that was previously not mentioned in other journal articles. However, the need for the private sector to not entirely rely on academia to fill the skills shortage is a repeating theme. The study also highlighted a need to reduce stress and improve mental health within the construction industry; however, the link to how this may reduce the impact of the skilled labour shortage is rather indirect.

In a bid to conceptualise the relationship between skilled labour shortages and project performance, Yusoff et al. [40] drew the conclusion that project-related factors like working conditions and stress levels also affected the availability of skilled labour. The major hurdles were found to be related to the economics of training. With a return on investment harder to quantify, contractors often find it difficult to justify the training costs [38,41]. As a result, on-the-job training is the most common form of workplace training, where training is integrated into everyday work functions rather than a standalone timeslot. This also helps us understand why systemically the construction industry seeks candidates with experience over those with less experience and more educational qualifications.

Research into innovative training programs is still in its early stages in Australia. Francis and Paton-Cole [22] investigated the 'Maker Immersion Program', which blends interactive training with VR/AR, as well as face-to-face learning. Whilst it explores why we need an immersive educational program, the process of identifying which content or skills should be delivered in an immersive way was out of scope.

Callan et al. [41] also conducted rather seminal research into blended forms of e-learning over a decade ago. Through 21 interviews, the articles affirmed the existence of a skills gap between what is offered by VET systems and what is required by the industry. The requirement for a cost-effective training methodology was argued, with the article calling for one that is easily deployable and effective. This is a predominant gap in the literature. Hou et al. [42] affirm that there is a scarcity in construction training tools and current approaches aligned with contemporary complex construction projects and activities. The study posits that this is a key reason for labour productivity issues in the construction industry. With the advent of modern learning methods, Poon [43] discussed the

redevelopment of civil engineering and construction management curricula in a UK university. The intention behind the redevelopment was to allow for flexibility and address the skills gap. Whilst the study was UK-based, with findings that cannot be directly applied in Australia, the study design is valuable to consider. Through an interview and case study-based research, the study confirmed that the UK construction sector also suffers from a skills shortage [43]. Despite a fall in job vacancies indicating increased employment, Poon [43] found that the vacant jobs were harder to fill. Hence, vacancy rates alone are not a good indicator of the skills gap. Poon [43] posits that education, especially life-long learning is vital for macro and micro economies such as companies.

Noting that the industry is often hesitant to invest in training [38,41], there needs to be stakeholder interaction between professional bodies, academia and industry. Poon's [43] market research found that there is a growing need for CPD in the form of short courses that can further benefit from flexible and modern learning [22,41,42]. However, identifying which skills need training remains an important requirement. Training needs analysis (TNA) was found to be a systematic process for identifying training requirements [44]. Albassami et al. [44] study how TNA can be used within construction firms. TNA is conducted at three levels: organisational, team and personal. Whilst their study aims to identify a skills gap among employees at a personal level, these skills are conceptualised to be applied in teams, within organisations. Hence the organisation and team level considerations are of value when investigating a personal level skills gap analysis. Albassami et al. [44] call for the following guide to identifying the training needs. Firstly to assess the organisational strategy and objectives. This includes strategic goals and business plans as employee skills are to ultimately support the organisation strategy in line with the RBV. Then to analyse job requirements by examining job descriptions and specifications of required skills and competencies. This is to be then compared with current performance of employees. Finally, to contextualise the findings by collecting stakeholder input from managers and employees to record perceptions of skills gaps.

2.2. Characterising the Skills Deficit in Construction

2.2.1. Broad Knowledge and Soft Skills Deficits

Distinguishing between high-level construction cognitive and hands-on practical skills can be important when analysing the skills gap [11]. However, Ding et al. [11] does not mention what the actual skills gap is. The study presents a list of shortages in construction professionals, such as project managers, rather than identifying specific skill deficiencies. Consequently, there remains a gap in understanding the actual skills that the construction industry lacks, which may contribute to the shortage of construction project managers. Baker et al.'s [45] qualitative analysis found that women often lack the technical skills and experience required for the construction industry, which poses a major barrier to employment. However, a notable omission is that even higher education graduates may face a considerable skills gap. Despite this, a major hurdle remains to be the lack of skills or experience these underrepresented demographics inherently face that is limiting them from being employed. The literature above also does not identify the skills these demographics are currently lacking and require training on. This is a notable limitation as to get them employed, they would need to have the skills that employers look for. Hence, identifying the skill needs from an employer point of view remains a vital objective.

Detsimas et al. [38] investigated the skills gap in the Queensland construction industry. This survey-based methodology affirms that there is a skills gap particularly in the generic skills area such as communication techniques, team building/people management/conflict resolution, problem-solving, time management, stress management and independent learning. It is important to note that this article shows how many employers expect employees to learn independently and consider this a general skill. However, much

of the learning happens on the job and relies on other skilled employees within a business that can act as mentors. Investigating this through the RBV lens, this implies that highest level of competency within an organisation is often capped by its most proficient employee. There is a need for formal training intervention. We et al. [46] reported that there is a skills gap in knowledge, particularly underqualification, where the industry needs surpass educational attainment. Hence, on-the-job training does not entirely mend the skills gap.

2.2.2. Technology, BIM, and Emerging Competencies

Abu Alieh et al. [47] compared the skills gap between academia and industry, restricted to the domain of BIM in Australia. Through 17 semi-structured interviews, they found that the lack of BIM skills was the major barrier for BIM implementation. A similar comparison can be drawn to the context of the skills gap epidemic where the lack of education and training is the major cause of the skills shortage. Abu Alieh et al. [47] recommended training as the solution to bridge the gap between the ‘demand’ and the ‘ability’. This study focuses on BIM skills in particular; however, through a macro lens it was found that there are other skills which also need scrutiny. The gaps that were identified as the most severe were construction technology, information technology, problem-solving skills, construction economics, risk management, basic theories, business management and sustainability science.

Through a systematic review of 53 Scopus articles, Vaz-Serra and Romero [48] deduced there were 306 skill gaps, of which all fell into the following categories: construction knowledge; management and communication; financial and legal; environment, culture and digital; personal attributes; and leadership. Of these, limited BIM knowledge, personal attributes such as leadership and certain hard skills were found to be priority gaps. This is a relevant finding related to the outcome of this research; however, it is limited by its currency, with this research being conducted before the global pandemic. The employers identified that there were notable gaps in graduates, including a lack of confidence, inability to communicate, a lack of basic construction knowledge, and a lack of professional writing skills. Numerous articles have attested to AI being able to help address the issue of employee skill adequacy [49–51]. Thus far, it is evident that the issues identified in studies that have analysed the skills shortage through an opinion-based employers’ lens [46,47,52] are able to be addressed efficiently through AI, helping to combat concerns from the industry such as a lack of capital for further training. The study mentions that VR/AR, like in the ‘Maker Immersion Program’ is a promising technology to explore, however does not consider what skills need to be taught using VR/AR. Hence a skills gap likely remains the initial step needed to design a contemporary training platform or framework for integration within construction organisations. It found that certain specialised areas require CPD in the form of flexible short courses. However, the only examples provided were geotechnical engineering, sustainability, flooding and transport. This suggests there is a need for geotechnical skills in the industry. Similarly, Omer et al. [53] presented a need for recyclable materials competency. A further skills gap analysis is required to validate these findings and explore additional skills that may be needed.

2.3. Methodological Approaches to Quantifying the Skills Gap

2.3.1. Qualitative and Expert-Based Studies

Historically, attempts to quantify the construction skills gap have predominantly employed experiment-, survey- or action research-based methodologies, which remain inherently subjective and prone to observational biases. With most of the literature conducting interviews and surveys as the main data collection method, Egbelakin et al. [34] employed Brain and Clarke’s [54] six-step thematic analysis process. The first step is to be-

come familiar with the data. Egbelakin et al. [34] examined the outcome of a workshop attended by 10 high-profile construction industry professionals. A notable limitation is that the workshop findings may present some biases, as they rely on 10 participants. The findings are also geographically limited to NSW, which, whilst relevant to this study, may not be applicable to other states in Australia, which have their own construction legislation. The survey yielded a substantial 655 responses. The second and third steps were to generate themes. Egbelakin et al. [34] underpinned their research by a thematic analysis of the interviews. The remaining steps involved reviewing the themes, defining them once finalised, and producing a scholarly report. The findings highlight persistent labour shortages and misalignment between existing workforce profiles and emerging requirements around sustainability, technology adoption and diverse participation.

There are similar studies that relied on manual thematic analysis to identify skill requirements, which limits sample size and scalability. For example, Salman et al. [55] utilised manual coding to analyse 70 job advertisements to inform a university residential construction curriculum. Their iterative thematic analysis generated 11 major skill themes, highlighting employer demand for software proficiency (e.g., Excel, Procore), risk management, and soft skills (teamwork and communication). While highly detailed, manual coding of 70 ads may struggle to capture macro-market trends.

McLaughlin's [39] study employed similar interviews of highly experienced personnel. Excluding young professionals means that there are inherent biases. It is reasonable to assume that these participants are highly skilled and so will not be able to relate to their under-skilled colleagues. However, this is also a strength as they are more likely to be able to recognise under-skilled workers and their implications within the industry. The macro-level skills gap in the industry was investigated by Wu et al. [46]. The article initially derived the skills gaps from a literature review and surveyed 253 graduates from various Australian universities to rank the gaps. Whilst the initial literature review from which the gaps were derived was not presented, it is not possible to verify their validity. The major limitation is that the interviews were only used to rank the gaps, as opposed to verifying them. As such, there is overall a low degree of empirical certainty regarding the skills gap despite the high number of survey participants.

Vaz-Serra and Mitcheltree [52] also conducted similar research, where their list of required skills for construction managers were obtained using survey questionnaires. These differences were largely due to the fact that these studies were opinion based. There remains a lack of objective skills gap analyses which this study seeks to directly address. Borg and Scott-Young [56] investigated the skills gap issue from the perspective of the employers. They interviewed 18 contractors and found that the skills demanded by the employers were empathic communication, passion and technical construction knowledge. The methodology consisted of a literature review of 23 articles to obtain 20 competencies, followed by a 120-response survey to validate the skills obtained. This article was based in Malaysia; as such, the findings have limited applicability in Australia. However, the statistical method used to quantify the competency gap was novel and has merit. Competency gap analysis is a method used to identify which skills need the most improvement within a team or organization. Individuals rate each required competency on two scales: how important it is for their role and how competent they currently feel, usually from 1 (low) to 5 (high). These ratings are then weighted and compared, so that for each competency, the gap between importance and current ability is calculated. The largest gap highlights where training or development efforts should be focused, ensuring that resources are directed toward the most crucial skill areas for job success. This study predominantly surveyed project managers to identify the competency gap in technical recyclable materials. As project managers are not actually involved in design work, this is

a considerable limitation, as individuals who do not demonstrate the competency are assessing its importance.

2.3.2. Curriculum and Competency Comparisons

Abu Alieh et al. [47] compared the skills gap between academia and industry, restricted to the domain of BIM in Australia. A major limitation of this approach is its reliance on employer perceptions to deduce student ability, which may introduce observational bias. Analysing the explicit learning outcomes of higher education institutions provides a significantly more objective measure of actual graduate capability. Papuraj et al. [20] demonstrate this by deriving the industry ‘demand’ by obtaining the skills from BIM BOK (body of knowledge). Vaz-Serra and Romero’s [48] research on the skills requirements of construction managers, in comparison to that offered by educational institutions showed that was little research comparing the two, calling for a skills gap analysis. In addition, this data was obtained through secondary research. The skills requirements vary rapidly across geographic regions and over time [48], so there is a requirement for an objective primary data-based skills gap analysis.

2.3.3. Job Advertisement and Labour-Market Analytics

A significant portion of recent literature relying on job advertisement data has utilised direct web-scraping techniques. However, this approach frequently introduces complexity regarding the Terms of Service (ToS) of major job boards. For instance, Oh et al. [57] and Verma et al. [58] extracted large datasets from platforms such as Indeed. Verma et al. [58] utilised the Indeed API to harvest URLs before deploying Python 3.12.13 scripts to locally scrape the job descriptions. Similarly, Yu et al. [59] used web scraping to gather data for unsupervised Latent Dirichlet Allocation (LDA) clustering, though the ToS compliance of their data source remains unverified. These methods, while yielding large datasets, often explicitly violate the policies of platforms such as Indeed. Conversely, Fleming et al. [60] demonstrated a more methodologically sound approach to data acquisition by specifically targeting engineerjobs.com, chosen explicitly because its ToS permitted automated data collection.

2.4. Natural Language Processing (NLP) and Taxonomic Frameworks

When extracting skills from unstructured text, the selection of the underlying NLP model is critical. LDA was ranked as the one of the better methods for extracting skills from job ads [61]; however, the output was also harder to delineate, with similar themes being categorized as different. BERTopic [62] was deemed as a suitable method that could consider the context of a sentence when extracting a skill. Hence, when mapping to a taxonomy, it was deemed appropriate. Raw job descriptions are unstructured; therefore, the literature emphasizes mapping extracted data to standardized taxonomic frameworks. Fleming et al. [60] successfully mapped engineering job postings to the U.S.-based ONET (Occupational Information Network) database, which provides standardised profiles for over 900 occupations. While ONET is a commonly referenced framework, it lacks localization for the Australian context. To address this gap, we adopted the Australian Skills Classification (ASC), providing a taxonomy that better reflects the professional environment of the Australian civil engineering and construction sectors.

To achieve scale, the field has transitioned to natural language processing (NLP). Zhang et al. [63] introduced SKILLSPAN, utilizing domain-specific language models (JobSpanBERT and JobBERT) trained on 3.2 million unlabelled job posting sentences and fine-tuned with 14,500 expert-annotated sentences. Their work validates BERT (Bidirectional Encoder Representations from Transformers) as the state-of-the-art methodology for extracting both hard and soft skills from unstructured text. Building upon this consen-

sus, this study utilises advanced Transformer models. While the JobSpanBERT model was not made publicly available, the JobBERT was accessible and applicable to this research.

Job2Vec [64] demonstrates how labour market representations can be enriched through multiple views, including semantic, graph-topological, and career-transition information. By proving that the structural relationship between skills is just as important as the skills themselves, Job2Vec provides the theoretical justification for this study's dual-method approach: capturing volume via semantic mapping, while capturing structural topology via network analysis (Betweenness Centrality).

Furthermore, quantifying the skills gap requires comparing two distinct corpora of text (Demand vs. Supply). Traditional sentence embeddings often struggle with complex, set-level logical operations. Recent advancements such as SetCSE [65] have demonstrated how contrastive learning of sentence embeddings can successfully support set-level operations. This works in specifically identifying the semantic intersections and differences between distinct groups of concepts. The theoretical architecture of SetCSE validates the necessity of moving beyond basic keyword matching, toward deep vector-space comparisons when analysing supply–demand disparities. Ultimately, it was decided not to use SetCSE here, as this would have resulted in the loss of the ability to map skills to a national taxonomy (ASC). Mapping all the skills to ASC allows for a standardised method of analysis that can be repeated in the future and easily compared with previous results, as ASC is fixed.

These methods demonstrate the growing sophistication of NLP-based labour market analytics. Nevertheless, this study adopts SBERT-based semantic mapping because the objective is not job-title benchmarking or supervised skill-span extraction, but the transparent mapping of demand and supply text to a nationally standardised taxonomy. The use of ASC categories requires auditability, making SBERT suitable for the present curriculum-alignment task

2.5. Research Gap

Existing studies have established that there is a skills shortage in the Australian construction industry [11,21,22,24]. The existing literature reveals that the skills that are in short supply have predominantly been obtained through secondary data and ranked or verified through subjective primary interview and survey data. While this critically verifies the skills gap, a degree of subjectivity and bias remains because of this methodology. The literature also repeatedly posted the need for periodic skills gap analysis every 6 months, with the frequency likely dictated by turnover rate and the rapidly evolving nature of the construction industry [23–25]. The literature proposes that companies should conduct the skills gap analysis every 6 months, with the high frequency likely dictated by turnover rate and the rapidly evolving nature of construction. This is in agreement with previous articles [23–25].

In summary, the literature repeatedly posits the need for periodic skills gap analyses, ideally every six months, due to the rapidly evolving nature of the sector. However, current literature often relies on subjective surveys or interviews. Therefore, there is a clear need for a scalable, computation-assisted skills gap analysis that reduces reliance on subjective perception while still supporting pedagogical judgment.

3. Methodology

3.1. Research Design

The methodology is summarised in Figure 1.

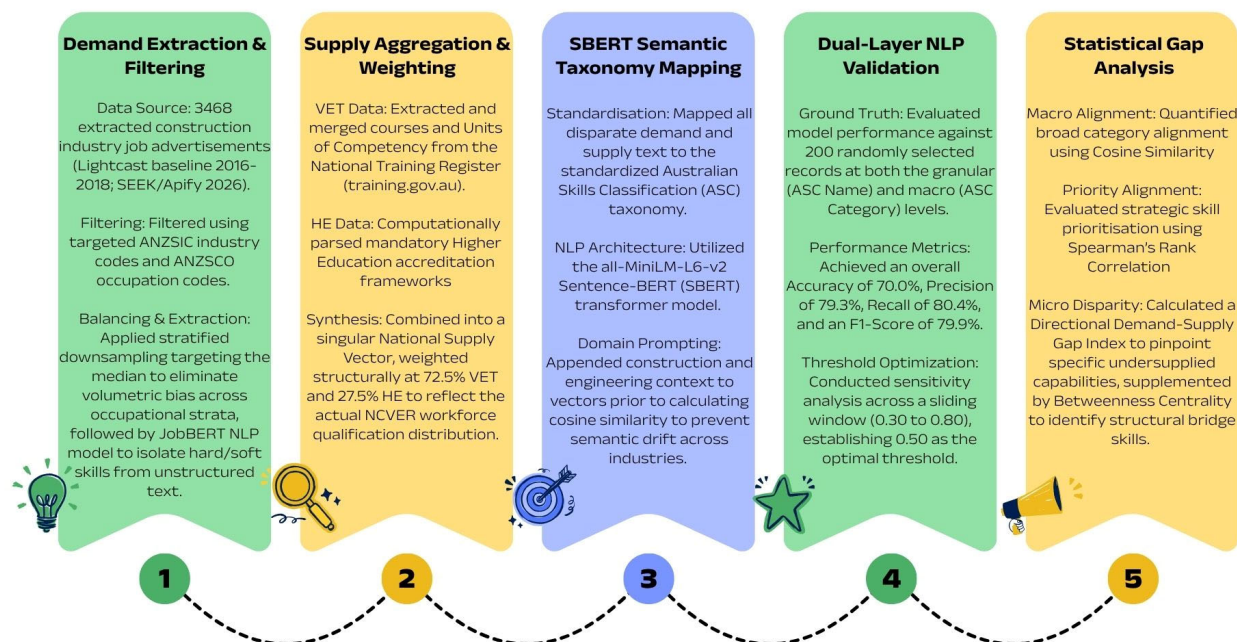


Figure 1. Overview of the methodology.

3.2. Stage 1: Establishing the Skills Demand

3.2.1. Data Population and Filtering

This research uses the proprietary Lightcast dataset and SEEK job advertisements for the Australian region. Historical baseline data (2016–2018) was sourced from the Lightcast database, while current data (2026) was carefully extracted from SEEK via Apify.

This study utilises publicly available job advertisement data collected from the SEEK platform. Data collection from SEEK was executed using an automated cloud-based wrapper. To ensure adherence to platform data governance, formal written authorisation was obtained from SEEK. Only publicly accessible and non-identifiable information was retrieved, and no personal, sensitive or confidential data were collected. All data were analysed in aggregated form to ensure that no individuals or organisations could be identified.

The Lightcast (previously Burning Glass) job advertisements database [66] is used by reputable public and private sector reports such as PWC, Infrastructure Australia and the Australian government treasury [7,67,68]. The database is also provided in a cleaned format, with unique records and numerous fields such as ANZSCO and ANZSIC and skills categories for all job ads. The initial dataset contained 29,660 records. Given that the initial dataset was not construction-specific, analysis began by cleaning and filtering the data further.

The data was initially loaded as a csv file onto Python, and a primary filter was applied to ANZSIC codes. Once the data was filtered to only show the codes in Table 1, the dataset was further filtered to retain the ANZSCO occupations shown in Table 2. The use of ANZSIC and ANZSCO codes allows for reproducibility and standardisation of the data. The literature review highlights skills and occupations that are industry-specific; however, this makes it difficult to compare results, as occupations and job titles are continuously changing. Hence, the use of these framework codes allows for national stand-

ardisation in Australia. Prior to filtering the raw data, there were 29,660 unique job advertisement records.

Table 1. ANZSIC category filters.

ANZSIC_1	ANZSIC_1_NAME	ANZSIC_3	ANZSIC_3_NAME
E	Construction	301	Residential Building Construction
E	Construction	302	Non-Residential Building Construction
E	Construction	310	Heavy and Civil Engineering Construction
E	Construction	323	Building Installation Services
E	Construction	324	Building Completion Services
E	Construction	329	Other Construction Services
M	Professional, Scientific and Technical Services	692	Architectural, Engineering and Technical Services

Note: ANZSIC_1 (industry division): the highest and broadest level of classification, denoted by a single letter. ANZSIC_1_NAME (division name): the descriptive title of the broad division category. ANZSIC_3 (industry group): a more granular, 3-digit breakdown of the broad division that groups businesses doing similar types of work. ANZSIC_3_NAME (group name): the descriptive title of the 3-digit industry group.

Table 2. ANZSCO occupation filters.

ANZSCO-6 Code	ANZSCO-4 Unit Group	ANZSCO Occupation Name	Category
133111	Construction Project Managers	Construction Project Manager	Strategic Management
133112	Construction Project Managers	Project Builder	Strategic Management
133211	Engineering Managers	Engineering Manager	Strategic Management
232111	Architects	Architect	Design & Pre-Construction
232112	Architects	Landscape Architect	Design & Pre-Construction
232212	Surveyors	Quantity Surveyor	Design & Pre-Construction
232213	Surveyors	Surveyor	Design & Pre-Construction
232611	Urban and Regional Planners	Urban and Regional Planner	Design & Pre-Construction
233211	Civil Engineering Professionals	Civil Engineer	Technical Professional
233212	Civil Engineering Professionals	Geotechnical Engineer	Technical Professional
233214	Civil Engineering Professionals	Structural Engineer	Technical Professional
233215	Civil Engineering Professionals	Transport Engineer	Technical Professional
233311	Electrical Engineers	Electrical Engineer	Technical Professional
233512	Mechanical Engineers	Mechanical Engineer	Technical Professional
233513	Mechanical Engineers	Production or Plant Engineer	Technical Professional
233914	Engineering Professionals	Environmental Engineer	Technical Professional
233915	Engineering Professionals	Naval Architect (Marine Designer)	Technical Professional
312211	Civil Engineering Draftspersons and Technicians	Civil Engineering Draftsperson	Technical Specialist
312212	Civil Engineering Draftspersons and Technicians	Civil Engineering Technician	Technical Specialist
312311	Quantity Surveying Technician	Quantity Surveying Technician	Technical Specialist

312312	Surveying Technicians	Surveying Technician	Technical Specialist
312912	Building and Engineering Technicians	Construction Estimator	Technical Specialist
331111	Bricklayers	Bricklayer	Core Trade
331112	Bricklayers	Stonemason	Core Trade
331211	Carpenters and Joiners	Carpenter	Core Trade
331212	Carpenters and Joiners	Joiner	Core Trade
331213	Carpenters and Joiners	Roofer	Core Trade
331311	Fibrous Plasterers	Fibrous Plasterer	Core Trade
332211	Glaziers	Glazier	Core Trade
333111	Air Conditioning and Mechanical Services Plumbers	Air Conditioning and Mechanical Services Plumber	Core Trade
333211	Drainers	Drainer	Core Trade
333212	Gasfitters	Gasfitter	Core Trade
333311	Roof Plumbers	Roof Plumber	Core Trade
333411	Plasterers	Plasterer	Core Trade
334111	Plumbers	Plumber (General)	Core Trade
334112	Plumbers	Pipelayer	Core Trade
334113	Plumbers	Gas Plumber	Core Trade
334114	Plumbers	Water Plumber	Core Trade
334115	Plumbers	Sanitary Plumber	Core Trade
341111	Electricians	Electrician (General)	Specialized Trade
341112	Electricians	Lift Mechanic	Specialized Trade
342111	Air Conditioning and Refrigeration Mechanics	Air Conditioning and Refrigeration Mechanic	Specialized Trade
511111	Contract, Program and Project Administrators	Contract Administrator	Project Support/Admin
511112	Contract, Program and Project Administrators	Program Administrator	Project Support/Admin
599612	Other Clerical and Administrative Workers	Project Administrator	Project Support/Admin
599613	Other Clerical and Administrative Workers	Construction Administrator	Project Support/Admin
821111	Construction and Mining Labourers	Construction and Mining Labourer	Labour/Entry-Level

Note: ANZSCO-4 (unit group): the 4-digit level of classification that groups together several closely related occupations sharing similar skill sets and core tasks. ANZSCO-6 (occupation code): the 6-digit level representing the most specific, granular classification of a single job. ANZSCO (occupation name): the descriptive text title of the specific occupation that matches the 6-digit code.

To extract 2026 job posting data from SEEK, the following keyword searches were used for each role category:

1. Strategic Management—("Construction Project Manager" OR "Project Builder" OR "Engineering Manager");
2. Design and Pre-Construction—("Architect" OR "Landscape Architect" OR "Quantity Surveyor" OR "Surveyor" OR "Urban and Regional Planner");
3. Technical Professional—("Civil Engineer" OR "Geotechnical Engineer" OR "Structural Engineer" OR "Transport Engineer" OR "Electrical Engineer" OR "Mechanical Engineer" OR "Environmental Engineer");
4. Technical Specialist—("Civil Engineering Draftsperson" OR "Civil Engineering Technician" OR "Quantity Surveying Technician" OR "Surveying Technician" OR "Construction Estimator");

5. Core Trade—(“Bricklayer” OR “Stonemason” OR “Carpenter” OR “Joiner” OR “Roofer” OR “Fibrous Plasterer” OR “Glazier” OR “Air Conditioning and Mechanical Services Plumber” OR “Drainer” OR “Gasfitter” OR “Roof Plumber” OR “Plasterer” OR “Plumber” OR “Pipelayer” OR “Gas Plumber” OR “Water Plumber” OR “Sanitary Plumber”);
6. Specialized Trade—(“Electrician” OR “Lift Mechanic” OR “Air Conditioning and Refrigeration Mechanic”);
7. Project Support/Admin—(“Contract Administrator” OR “Program Administrator” OR “Project Administrator” OR “Construction Administrator”);
8. Labour/entry-level—(“Construction Labourer” OR “Construction and Mining Labourer”).

3.2.2. Stratified Sampling

A preliminary review of the raw Lightcast job advertisement dataset revealed a significant imbalance across the targeted occupational groups. Due to the organic disparity in job advertising, where high-turnover roles such as ‘Core Trades’ generate more listings than ‘Strategic Management’ or ‘Design & Pre-Construction’ roles, the raw dataset was skewed. If processed without normalization, this disparity would introduce a bias, causing the resulting skills demand to disproportionately reflect certain categories of trade while obscuring the requirements of professional and managerial roles.

To mitigate this bias, a stratified sampling methodology was employed. The dataset was first stratified into discrete occupational subgroups based on their ANZSCO codes, shown in Table 2 (e.g., Technical Professional, Technical Specialist, Core Trade).

To achieve an even representation without excessively discarding data, the target sample size per stratum, n_{target} , was established as the median of the initial stratum sizes.

The final sampled size n_i , for each occupational category S_i , is therefore defined as a piecewise function, ensuring that categories with less jobs are retained in full, while categories with more jobs are randomly down-sampled without replacement.

Under this framework, if $N_i > n_{\text{target}}$, a random sample of size n_{target} is extracted from S_i . Conversely, if $N_i \leq n_{\text{target}}$, all N_i observations are retained. The total size of the final balanced dataset, n_{total} , is thus the sum of the newly bounded strata.

This ensures that subsequent skills demand analysis contains fewer biases resulting from the uneven extraction of job categories.

3.2.3. Skills Taxonomy

The Lightcast dataset provides skills as obtained from the job advertisements. These skills were obtained by parsing job advertisements through the Lightcast skills API. This API is trained on 3 billion global job postings, mapping against 34,000 skills and over 1800 unique occupations [69]. This was provided automatically as part of the dataset and was not performed by the authors. The author conducted a manual review of random job postings to verify that the extracted skills accurately reflected the original advertisements. This randomised verification approach is used to ensure a high level of accuracy in the API outputs. The ‘Align My Curriculum’ (ACM) framework [70] takes a similar approach mapping job ads to skills categories. However, it does so by mapping the job role to only one skill category. This is less accurate, as job roles often require multiple skills; hence, a granular analysis of the job description, as opposed to the role title, is required to map skill requirements

To isolate the skills from the unstructured SEEK job description text (of the 2026 job advertisements), this study deployed the domain-adapted NLP model developed by Zhang et al. [63] for the SKILLSPAN dataset. The unstructured job text was processed

sequentially through the authors' officially fine-tuned sequence-labelling models: `jobbert_skill_extraction` and `jobbert_knowledge_extraction`.

It should be noted that while Zhang et al. [63] identified a SpanBERT-based architecture (JobSpanBERT) as the optimal model for detecting multi-word contiguous spans, the fine-tuned model was not released to the public repository. Consequently, to maintain reproducibility and avoid manually retraining the model from scratch, this study utilized the officially released, fine-tuned standard BERT models (JobBERT). Despite this architectural limitation, these domain-adapted models represent the current state of the art in out-of-the-box competency extraction, successfully isolating both hard/soft skills and technical knowledge components.

The use of JobBERT for 2026 SEEK postings aligns with SkillSpan's finding that domain-adapted models outperform non-adapted language models for job-posting skill extraction. However, once the skills were extracted, SBERT was used for taxonomy mapping to preserve comparability across Lightcast skills, SEEK-derived skills, VET unit titles and HE accreditation statements.

A key drawback of skill identification is the possibility that skills are fast evolving and specific. For example, skills such as AutoCAD, BIM and Primavera P6 are mentioned in the database, despite all falling into the broader category of digital skills. These skills are market-driven, granular and rapidly evolving (for example, whereas previously MS Projects was widely used, the industry now uses P6). This makes further standardised analysis challenging. Hence, this research uses the Australian Skills Classification Taxonomy [71] to categorise these skills into standardised and comparable categories. Using the Australian Skills Classification Taxonomy methodology statement [71], the granular job advertisement skills were fit into three major categories: core competencies, specialist tasks and technology tools. Within these categories, there were numerous other unique subcategories within which the granular skills were mapped. These subcategories were derived from the ASC and were chosen methodologically to standardise the results and contextualise them within the Australian construction industry.

The challenge, however, is that the database contains over 1000 unique skills, which makes manual mapping to ASC categories and skills very difficult. Hence, this research employs an automated semantic mapping process instead. The Python script loaded a pre-trained Sentence-Transformer which used the 'all-MiniLM-L6-v2' model. This model is used for semantic similarity, clustering, and retrieval tasks. It is more accurate than the standard BERT model and is highly effective for this sentence similarity task [72]. Its selection was based on efficiency, reproducibility and suitability for high-volume semantic comparison. The allMiniLM-L6-v2 model uses a specialised natural language processing method called Sentence—Bidirectional Encoder Representations from Transformers (S-BERT). The BERT technique was initially conceptualized by Devlin et al. [73], which was later improved by Reimers & Gurevych [74] to use cosine similarity to make the semantic comparison more efficient. This reduced the time required to find the most similar pair from 65 h for BERT to 5 s for S-BERT whilst maintaining accuracy.

The S-BERT model was fed the official skills definitions from the Australian Skills Classification Taxonomy, which the model then converted into a vector v , as shown in (1), in an n -dimensional space. A similar operation was performed for the job posting skills, which were converted into vector u , as shown in (2). The cosine similarity between two non-zero vectors u and v was then calculated, as shown in (3).

$$v \in R^n \quad (1)$$

$$u \in R^n \quad (2)$$

$$\text{Sim}(u, v) = \frac{u \cdot v}{\|u\| \|v\|} \quad (3)$$

The above cosine similarity equation yields a score between −1 and 1. The closer the score is to 1, the more similar the meaning is, in which case the highest score results in skill u being assigned to skill v . Domain prompting was also used in this study, whereby keywords such as “construction, engineering, project management” were appended to the skills so that the SBERT model could understand their domain context. In this analysis, a cut-off score of 0.5 was used. Only matches made with a similarity of over 0.5 were retained.

To further ensure rigour, a random manual review was conducted by the author to ensure that mapping was accurate and objective. This suggested acceptable accuracy; however, there was a degree of subjectivity. For example, the job posting skill ‘mentoring’ was mapped to the ‘teamwork’ within the Australian Skill Classification. Some authors argued that it could be mapped to the ‘coach others’ Australian Skill Classification instead. Given that even humans do not reach a final objective verdict on the mapping of skills such as these, the S-BERT mapping was deemed accurate and was retained for the remainder of the analysis.

3.2.4. Frequency and Thematic Map

To establish the objective skills demand, this step identifies the magnitude and location of the skills. Using Python, the magnitude of the skill occurrence was presented as a Pareto chart. By presenting the magnitude of the skill occurrence and the cumulative percentages, the Pareto chart can help identify the top 20% of the skills demand concentration that account for 80% of the total skills demanded by the industry. This is important to meet objective 1 as it would be impractical for curriculum to cover all skills explicitly demanded by the industry. Hence it is vital to make sure that the top 20% of skills are represented in the skills supply.

Given the dataset also contained location data, this study employs a geospatial analysis to produce a thematic map. Initially, a GeoJSON file is imported into the Python code to outline the Australian map and its states. This file also contains metadata on Australian states and territories, which is then compared with the job posting data’s state and territory field to map the spatial distribution of skill demand.

This study distinguishes between ‘absolute volume’ and ‘relative intensity’. A limitation of using ‘absolute volume’ for the thematic map is that this includes population-dependent biases. Regions with larger economies (e.g., New South Wales, Victoria) inherently generate higher frequencies for all skill categories simply due to the size of their labour markets. This masks the characteristics of smaller regional economies. To control for this bias, we let C represent the set ASC Skill Categories (e.g., Technology Tools, Core Competencies). Let R represent the set of all geographic regions (states/territories). For a specific skill category $c \in C$ in a specific region $r \in R$, the relative demand share $S_{c,r}$ is calculated as shown in (4).

$$S_{c,r} = \left(\frac{n_{c,r}}{N_r} \right) \times 100, \quad \text{where } N_r = \sum_{\{i \in C\}} n_{i,r} \quad (4)$$

$S_{c,r}$ is the percentage share of the skills demand for skill category ‘ c ’ in region ‘ r ’. $n_{c,r}$ is the frequency of count of skill category ‘ c ’ in region ‘ r ’. N_r is the total count of all skill mentions in region ‘ r ’.

3.2.5. Temporal Analysis

To quantify the trend in skills demand, a temporal velocity analysis was conducted. The challenge was distinguishing between a general increase in job posting volume and a specific increase in a skill category. To control for annual fluctuations in total job ad vol-

ume, this study utilised a relative approach rather than raw frequency counts. The relative demand share $P_{c,t}$ was calculated as shown in (5).

$$P_{c,t} = \left(\frac{n_{c,t}}{N_t} \right) \times 100, \quad \text{where } N_t = \sum_{i \in C} n_{i,t} \quad (5)$$

$n_{c,t}$ represents the frequency count of skill category 'c' in year 't'. In this context, Skill Velocity V_c is defined as the rate of change of the relative demand share over time. It represents the gradient of the trend line derived above and is calculated as shown in (6).

$$V_c \approx \frac{\Delta P_c}{\Delta t} \quad (6)$$

A positive ($V > 0$) indicates an emerging skill category. The category captures a larger share of the total demand. A negative ($V < 0$) indicates a declining skill category. The category becomes relatively less important to the industry's needs.

The temporal analysis is important for objective 3 to ensure that curriculum reforms are in step with industry demands. For example, if the temporal analysis presents a growth in digital skills demand in the past year, whilst the average curriculum reform period is 2–5 years, this shows that traditional education is too slow to catchup, providing a strong motivation for AI-powered training in objective 4.

3.2.6. Structural Network Analysis

A co-occurrence network analysis and a salary elasticity test of the skills were conducted. While frequency analysis reveals the volume of demand, this phase uncovers how skills connect to one another.

The structural network analysis mapped the structure of the skill demand to identify 'bridge skills' that connect skill clusters. Using the 'networkx' version 3.6.1 library in Python, originally developed by Brandes [75], a co-occurrence network, defined as $G(V, E)$, was constructed. In this graph, the nodes V represent individual skills mapped to their ASC categories, while the edges E represent weighted connections based on the frequency with which two skills appeared together in the same job advertisement.

To identify bridging skills, 'betweenness centrality' was calculated for every node, utilising the method formalised by Freeman [76]. 'Betweenness centrality' measures the extent to which a skill lies on the shortest path between other skills. Betweenness centrality $C_B(v)$ for a skill node v is calculated as shown in (7).

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \quad (7)$$

σ_{st} is the total number of shortest paths from skill s to skill t . $\sigma_{st}(v)$ is the number of those paths that pass through skill v . A high score indicates that certain skills are more important to connect other skill clusters, highlighting an area for curricula focus. This is visualised in Figure 2.

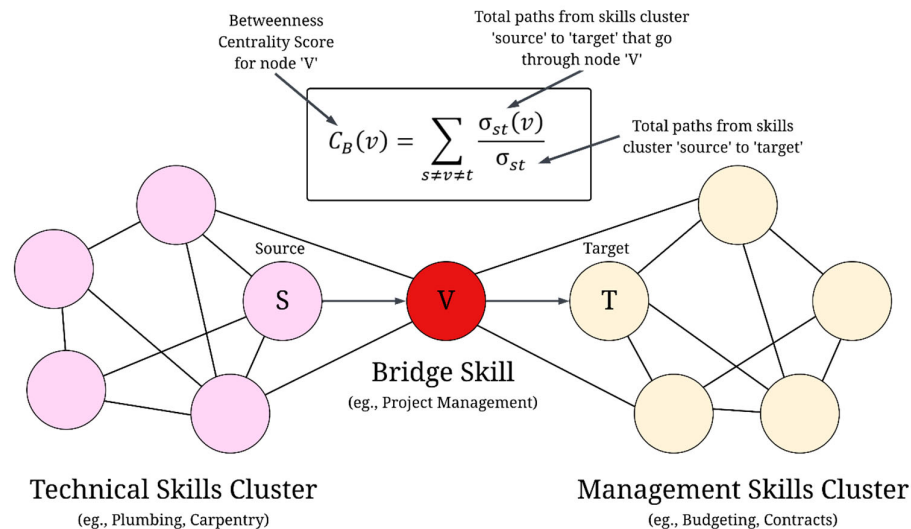


Figure 2. Betweenness centrality visualised in context.

Salary–Skill Elasticity Modelling was used to quantify the economic incentive associated with specific skills. Here, a linear regression analysis was performed. This model estimates the increase in advertised salary when a particular skill is requested in a job posting. The data preparation involved isolating job postings with valid salary data and converting text-based skill lists into numerical features using One-Hot Encoding.

An ordinary least squares regression model was then trained using the scikit-learn library. The relationship is modelled as shown in (8).

$$Y_i = \beta_0 + \sum \beta_j X_{ij} + \epsilon_i \quad (8)$$

Y_i is the maximum advertised salary, and X_i is a binary indicator for the presence of skill j . For example, if a job asks for ‘Contracts’ skills, then $X = 1$; otherwise it is assigned a value of 0. The coefficient β_j represents the salary premium associated with that skill. A positive, significant coefficient provides statistical evidence that a skill has economic value, validating the need for its inclusion in training. β_0 is the base salary without the premium for a specific skill, and ϵ_i is the error.

To further validate the dependency between skill categories and high-value roles, a Pearson’s Chi-square test of independence was conducted. The Chi-square statistic was calculated to determine if the observed frequency of skills in high-salary roles significantly deviated from the expected frequency. A result of $p < 0.05$ confirms that the demand for a certain skill is statistically dependent on the salary level. This analysis provides an economic substantiation for the proposed AI training intervention to target these specific competencies.

3.3. Stage 2: Establishing the Skills Supply

To allow for a like-for-like comparison, the skills supply is mapped in a comparable way. Human Capital theory [26] consists of four key components: education and training, skills and competencies, experience and health. Among these, skills and competencies are often derived from either experiences gained over time or education. Given that there is a decline in productivity in Australian construction, with a considerable proportion of the workforce on the brink of retirement [6,8], experiential learning cannot be relied upon. Hence, this study comprehensively maps the higher education (HE) and vocational education training (VET) institutions.

This study recognises that job advertisements and curriculum/accreditation documents are incomplete substitutes for skill demand and supply. Job advertisements may omit tacit or assumed skills, while accreditation documents may understate skills embedded within individual units, assessments, studio tasks or work-integrated learning. These sources are therefore treated as formal textual signals of demand and supply, rather than representations of workplace practice or curriculum delivery.

3.3.1. Mapping the VET Skills Supply

From training.gov.au, which is a government-run website, the National Training Register (NTR) was extracted. The NTR consisted of over 120,000 unique rows of data, which included courses, qualifications, units and skills. It also included important metadata, such as the currency of the course, the data revised and superseded. Similarly, a Unit of Competency (UOC) database was extracted, which contained over 150,000 unique rows of UOCs mapped to each course. The UOC database consisted of UOC metadata, such as the title of the competency, the currency, and whether it was a core or elective competency. However, it failed to contain any course-related metadata.

A Python code cell was used to merge the two databases to create a comprehensive list of courses mapped to UOC with both relevant metadata. This script then filtered for courses which fell within the ANZSCO occupation categories presented in Table 2, which were also used to filter the job postings, to ensure rigour. This ensured that the VET courses being mapped explicitly prepared students for the occupations presented in the filtered job postings. The Python script then loaded a pre-trained Sentence-Transformer, which used the all-MiniLM-L6-v2 model, via the SBERT library, to map each UOC title to the relevant ASC skill category. This process is also identical to the one described in Section 3.2.3 for the mapping of skills demand from job postings. This allowed for a granular mapping of not only the learning outcomes of each VET course but also the key skills acquired from each UOC to ASC skill categories across the entire VET sector.

3.3.2. Mapping the Higher Education (HE) Skills Supply

The HE skills supply was more challenging to map, as there is no single register that maintains a list of university degrees and the learning outcomes of all the UOC taught as part of each course. Web scraping violated the terms and conditions of most universities. In addition, due to dynamic JavaScript-based search functions within each university course handbook, bulk downloading a register through programming was not possible. University course descriptions were also often inconsistent, varying by institution and marketing language.

To establish a standardised HE supply of skills, this study analysed accreditation standards instead. The following source data were used:

- Engineering: Engineers Australia Stage 1 Competency Standard.
- Architecture: AACA National Standard of Competency.
- Construction Management: AIB Accreditation Standards.
- Quantity Surveying: AIQS Competency Standards.

These documents represent the mandatory minimum curriculum that every accredited degree in Australia must deliver. Hence, whilst granularity is lost, it helps to robustly map the entire HE skills supply. The pypdf library was installed so that all the raw text from the PDF layers could be extracted. The challenge here is accreditation standards are published as unstructured PDF documents, containing noise (preambles, submission guidelines and page footers) mixed with actual skills definitions.

A Python code cell heuristically filtered the data by removing short headers containing fewer than 20 characters and paragraphs containing over 300 characters. A keyword

search was then used to filter for verbs such as ['competency', 'standard', 'ability to', 'demonstrate', 'knowledge of']. The Python script then loaded a pre-trained Sentence-Transformer model (all-MiniLM-L6-v2) from the SBERT library and used it to map each UOC title to the relevant ASC skill category.

3.3.3. Aggregating the VET and HE Skills Supply

To facilitate a direct, macro-level comparison against industry demand, the VET and HE datasets were aggregated to form a singular skills supply vector. A 1:1 concatenation would introduce a volumetric bias, as university accreditation standards (e.g., Engineers Australia, AIQS) are inherently more general and generate significantly fewer data points than VET units.

A weighted aggregation model was applied to reflect the actual educational composition of the targeted workforce. As this research targets the entire construction sector, workforce data for both 'Architecture and building' and 'Engineering and related technologies' was extracted from the National Centre for Vocational Education Research [77].

A combined workforce of approximately 3.18 million personnel with known qualification levels was identified. Of this combined pool, 2.30 million held vocational qualifications, and 0.87 million held university degrees. Consequently, a normalized weight of 0.725 was applied to the VET supply distribution, and a weight of 0.275 was applied to the higher education (HE) accreditation supply. This weighted vector should be interpreted as a structural approximation of national education provision rather than a real-time curriculum inventory.

To ensure the validity of the VET to HE ratio of 72.5% VET and 27.5% HE workforce distribution baseline, a weighting sensitivity analysis was conducted. The educational supply vectors were re-weighted and evaluated across a spectrum of scenarios. This ranged from highly trades-dominant scenarios (90% VET/10% HE) to highly HE-dominant scenarios (30% VET/70% HE). Across all scenarios, the cosine similarity and Spearman's rank correlation coefficient exhibited stability. The cosine similarity remained between 0.36 and 0.41, while the Spearman's rank correlation coefficient remained between 0.22 and 0.25. This is shown in Figure 3.

Both the VET and HE frameworks dedicate a majority of their curriculum to specialist tasks. As such, altering the proportionate weight between them does not resolve the fundamental undersupply of Technology Tools and Core Competencies.

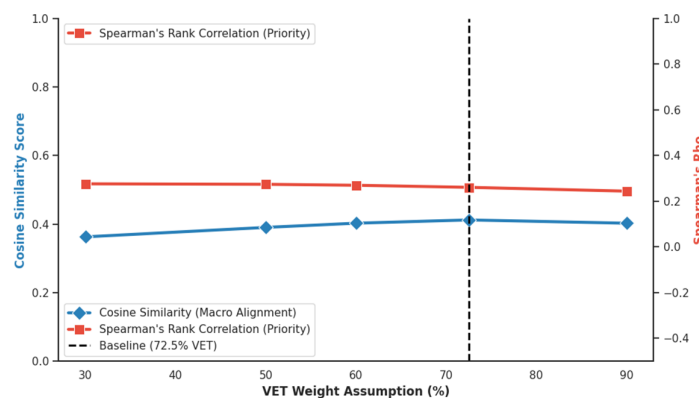


Figure 3. Weighting sensitivity analysis of VET/HE ratio against Spearman's rank correlation coefficient.

3.4. Stage 3: Quantifying the Disparity in Skills Demand and Supply

3.4.1. Macro Alignment

Due to the large number of job postings data and the relatively small number of VET and university courses available to service the demand, frequency-based analysis is not sufficient to analyse the gap in skills [78]. Jaccard Similarity also falls short, and for this reason, it is not used in this research as it is sensitive to the size of the sample.

Cosine similarities (CSs) are used instead. CS is widely used in the literature to adopt a standardised method of skills comparison [70,79]. The cosine_similarity module from the sklearn.metrics.pairwise package was imported. The model was fed the skills demand from job postings, which the model then converted into a vector v , in an n -dimensional space. A similar operation was performed for the skills supply from VET and university courses, which was converted into vector u . The cosine similarity between two non-zero vectors, u and v , was then calculated.

The result of the CS is a value between 1 and 0, where 1 shows perfect alignment and 0 shows no alignment. Given the importance of visualising the skills mismatch [70], a bar chart of CS values for ASC categories was produced.

For a more granular analysis of the top 20 most demanded industry skills, a CS analysis cannot be performed, as that would yield binary values for each skill. Hence, the skills demand and supply are compared via ranked importance instead [80,81]. The results are presented via a dumbbell chart and a bump chart. The bump chart offers a more discrete view of the comparative ranking of skills demanded in jobs postings and provided in education. The dumbbell chart facilitates gap analysis, showing the disparity in the rankings. Spearman's rank correlation (ρ), as shown in (12), is also calculated for both the top 20 skills and all skills. This is used to measure priority alignment between the supply and demand. This analysis is solely based on the rank of skills in both demand and supply, omitting the raw numbers. For example, if communication skills were ranked 1st in the supply with over 100 records tagged and were also ranked 1st in the demand with only 10 tagged records, Spearman's rank correlation (ρ) would show a high degree of alignment regardless of the raw numbers.

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (9)$$

In the above equation d_i is the difference in rank for a specific skill i , and n is the number of skills being compared. Where $-1 < \rho < 1$, a value equal to 1 implies perfect alignment, 0 implies randomness, and -1 implies inverse alignment.

3.4.2. Directional Skills Gap

To address the limitation that rank correlation measures ordinal priority but obscures the actual volumetric magnitude of the discrepancy, a Directional Demand–Supply Gap Index was used.

The gap score for any given skill i was calculated as the percentage point difference between its industry demand share and its weighted curriculum supply share.

$$Gap_i = D_i - S_i \quad (10)$$

This metric provides an indicator of directional skill gaps. A positive value indicates an undersupply, where a skill is demanded by employers at a significantly higher volume than it is represented in the curriculum. A negative value indicates a potential oversupply, where the educational system allocates a high proportion of curriculum space to a concept that employers rarely explicitly request. A near-zero value indicates optimal strategic alignment between the sector's training volume and market demand. This metric complements cosine similarity and Spearman's rank correlation by identifying the direction and magnitude of skill mismatch.

When interpreting these alignment metrics, it is important to distinguish between three distinct tiers: (1) documented educational supply (the formal textual accreditation and competency frameworks analysed in this study); (2) actual curriculum delivery (the granular teaching occurring within lectures, studios, and labs); and (3) graduate competence (the skill level practically acquired by the student).

HE accreditation standards operate at a significantly higher level of brevity compared to the detailed VET competency units. As a result, the comparison is subject to document-granularity bias. This bias could lead to an underrepresentation of specific, granular skills, such as Technology Tools skills, within the HE supply vector. While universities likely embed specific software and digital tool training within their actual curriculum delivery, these granular details are omitted from broad accreditation frameworks. Consequently, the results presented in this research analyse the documented skills gap.

3.5. Validation

To ensure the validity of the SBERT mapping, a validation protocol was implemented. Using Python code, the authors generated a random sample of 200 job-ad-to-ASC-skill pairs. This sample included both high-confidence and low-confidence scores of matches and non-matches. The author manually reviewed these 200 pairs to assign a binary rating of 1 for match or 0 for non-match. The performance of the model was evaluated using a 2×2 confusion matrix, shown in Figure 4, at a cosine similarity threshold of 0.50.

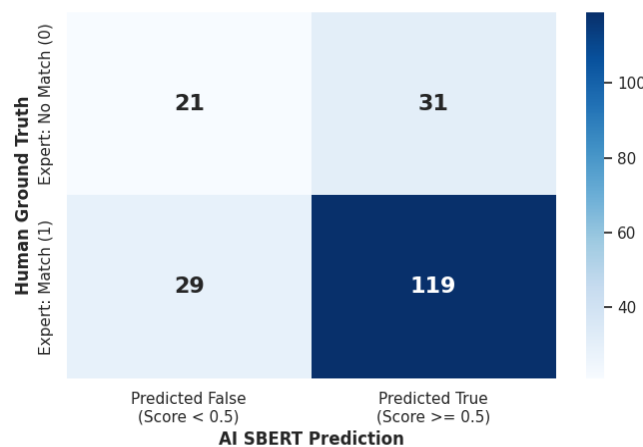


Figure 4. Confusion matrix at a cosine threshold of 0.50.

Overall, the model achieved a high degree of mapping reliability. This registered a precision of 79.3%, a recall of 80.4%, and a consolidated F1-score of 79.9%. This combined F1-score is considered suitable for this research. Whilst an F1-score over 90% is ideal, for classification tasks such as the one uses here, this was deemed good [82]. Category-level performance was also calculated. The mapping remained robust across all three ASC categories: specialist tasks (F1: 81.5%), core competencies (F1: 73.3%), and technology tools (F1: 73.3%). The results are summarised in Table 3.

Table 3. ASC category level performance.

ASC Category	Precision	Recall	F1
Specialist Task	0.808	0.822	0.815
Core Competency	0.917	0.611	0.733
Technology Tool	0.611	0.917	0.733

A sensitivity analysis was performed on the cosine threshold. This is shown in Figure 5. It was found that at lower thresholds, the model mapped almost everything it encountered. This resulted in a very high recall (near 100%); however, precision was very low. The model allows for too many false positives. At higher thresholds, while precision briefly climbs because the model only accepts near-perfect semantic matches, recall rapidly plummets. The 0.50 limit represents the critical intersection where the trade-off is neutral. At this exact point, the methodology retains the maximum volume of legitimate skills data (~80% recall) while maintaining a strict enough boundary to keep the false positive rate low (~80% precision).

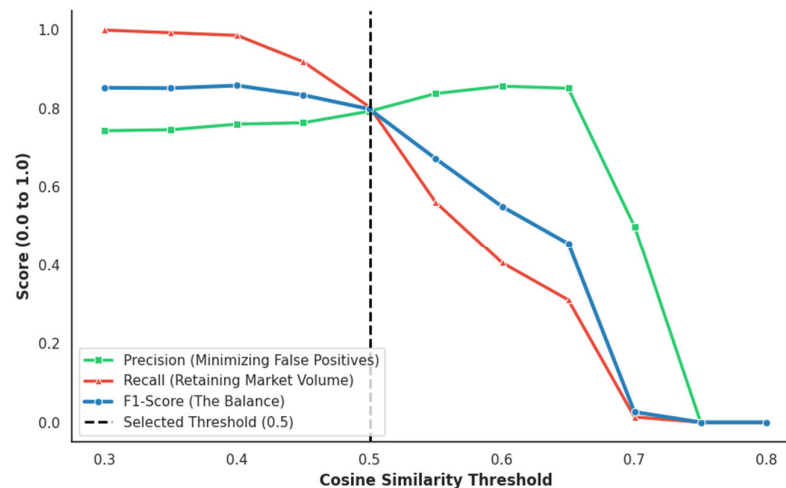


Figure 5. Cosine sensitivity threshold and its impact on precision, recall and F1-score.

4. Results and Discussion

4.1. Stratified Sampling Results

Figure 6a shows the 2016 job advertisements organised by occupational categories. As shown in the figure, the sample is heavily skewed by project support/admin roles (39%). If analysed, then the demand skills are more favourable to project support/admin roles.

Figure 6b shows the job ads found in the 2016 Lightcast sample after stratification, where the number of job advertisements per occupational category was more evenly distributed. This resulted in a reduction in project support/admin roles to 15% of the sample,

A similar pattern is shown in Figure 7a,b. However, as the 2026 job advertisements were extracted through SEEK, the extraction parameters were set to 300 jobs per category. This process resulted in 1710 job ads from 2016–2018 (referred to as the 2016 or pre-COVID data), whereas previously this was 2890. In addition, there were 1758 job ads from 2026 (referred to as the 2026 or post-COVID data), which was unchanged from the previous dataset. The two data periods are defined in Section 3.2.1.

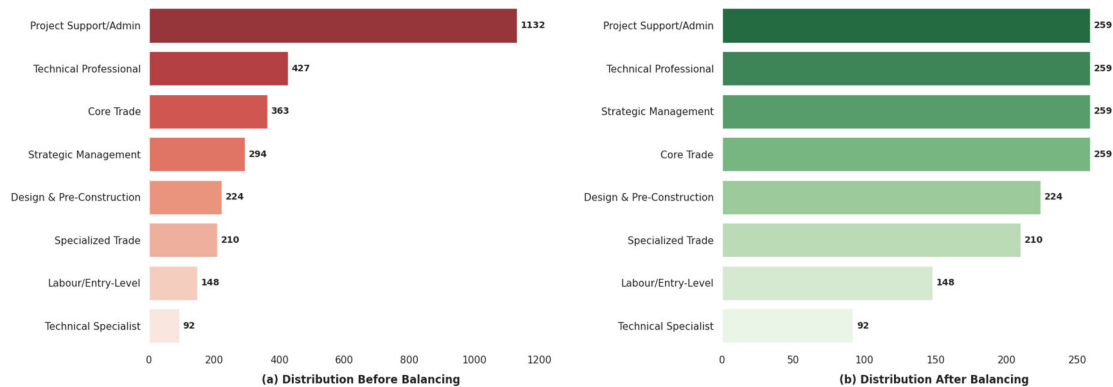


Figure 6. (a) 2016 job sample distribution before balancing. (b) 2016 job sample distribution after balancing.

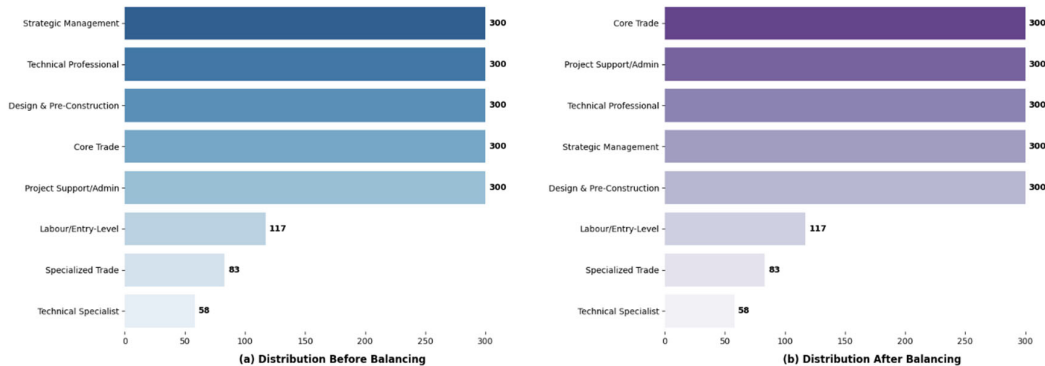


Figure 7. (a) 2026 job sample distribution before balancing. (b) 2026 job sample distribution after balancing.

4.2. Demand-Side Analysis: Job Posting Data

Objective 1 was achieved by conducting a frequency, spatial and temporal analysis of the job postings data. The frequency analysis of the 2016–2018 sample, presented as a pareto chart in Figure 8, demonstrated that employers predominantly sought Specialist Task (ST) skills, followed sequentially by core competencies (CCs) and technology tools (TTs). The red line represents the cumulative percentages, typical of a Pareto chart. Geographically, the spatial analysis revealed that Victoria and New South Wales drove the national demand for ST and TT skills, accounting for the highest proportion of these requirements (Figure 9).

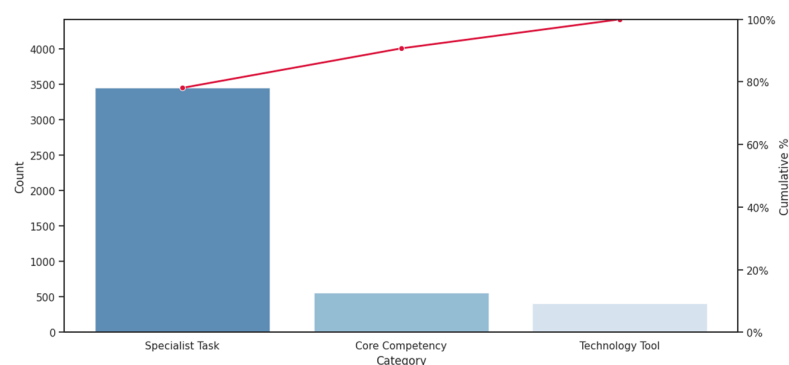


Figure 8. 2016 job advertisement mapped to ASC categories and overlaid with a Pareto chart.

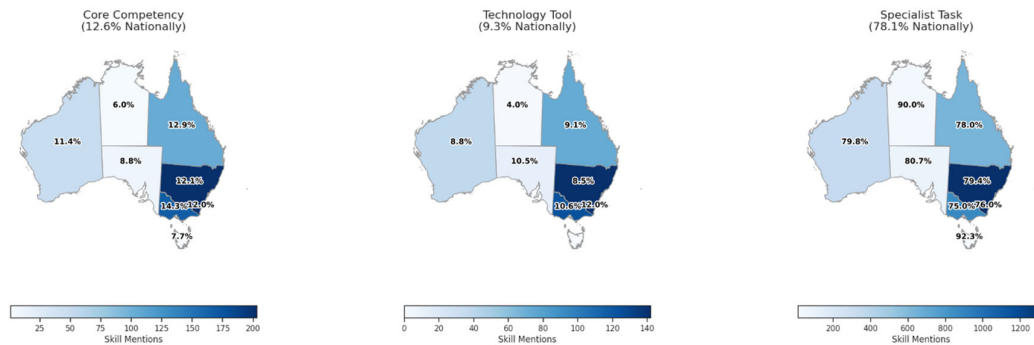


Figure 9. The 2016 spatial distribution of skills demand in Australia.

The 2026 sample revealed a similar trend. As shown in the pareto chart in Figure 10 (The red line represents the cumulative percentages) and the spatial distribution map in Figure 11, ST skills demand drove the sampled construction job market. This was followed by an identical second priority for CC skills and third priority for TT skills. This dominance of ST skills computationally validates the report by Master Builders Australia (2024) [21], which highlighted an immediate shortfall in the trades and operational sector requiring urgent workforce growth. Interestingly, NSW and Queensland drove the skills demand. This is in line with the infrastructure pipeline with Queensland's pipeline alone reaches over \$127 billion [83]. With NSW and Queensland's infrastructure pipeline soaring over the other states, the analysis validates that skills demand spatially coincides with a growth in construction project pipelines.

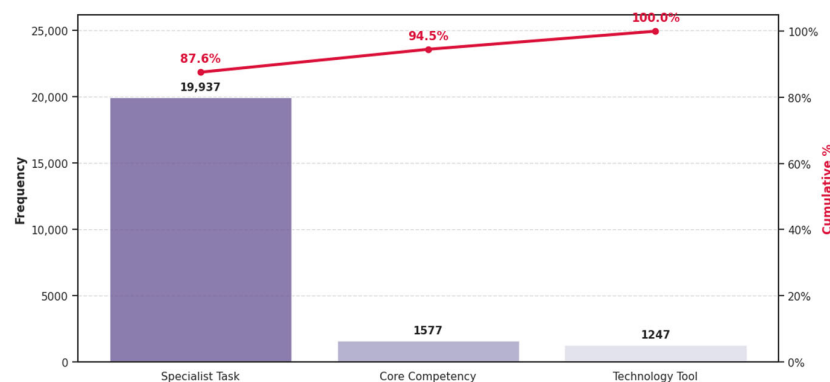


Figure 10. 2026 job advertisement mapped to ASC categories and overlaid with a Pareto chart.

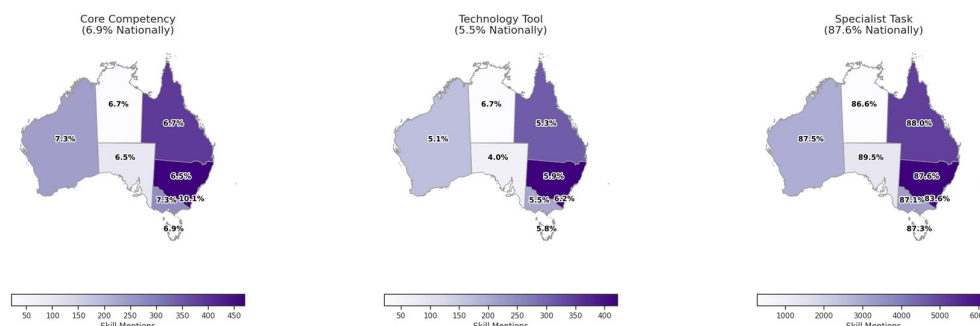


Figure 11. 2026 spatial distribution of skills demand in Australia.

This data-driven analysis allowed for a more granular extraction of skills mapped to the standardised ASC taxonomy. The frequency ranking of the top 20 in-demand skills is

shown in Figures 12 and 13. The results revealed that the management and coordination of construction work activities emerged as the most required skills in both the 2016–2018 and the 2026 job posting samples. The existing literature frequently highlights the need for specific proficiencies, most notably BIM [20,47]. BIM and other technology-related skills were not observed in the top 20 most in-demand skills in either sample. ST skills such as geotechnical engineering, sustainability, and transport [43] were also commonly cited as a major skill demand within the industry. This was validated by the samples and appeared under various ASC categories such as engineering research, engineering work and review of technical designs and processes. Within the CC skill category, the literature presented problem-solving, emotional intelligence and communication [52,56] as vital skill gaps in the construction sector. This was also validated in the samples, with communication ranked as a high-priority skill in both the 2016–2018 and the 2026 job advertisement samples.

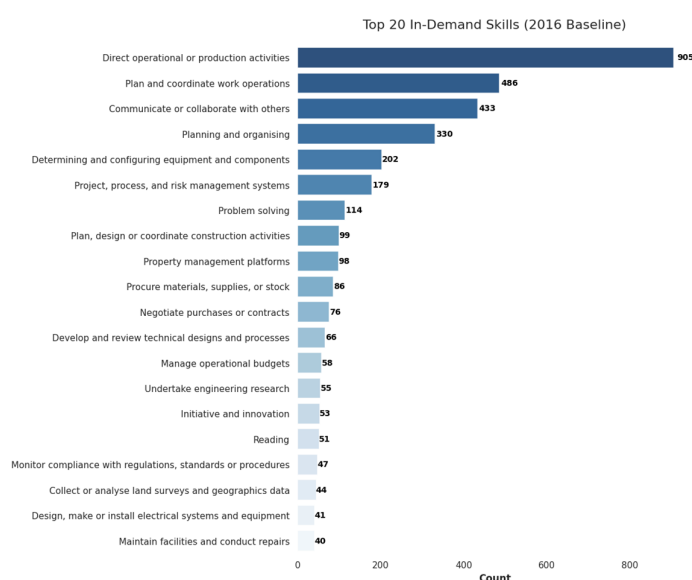


Figure 12. Top 20 most frequently demanded industry skills in the 2016 job advertisement sample.

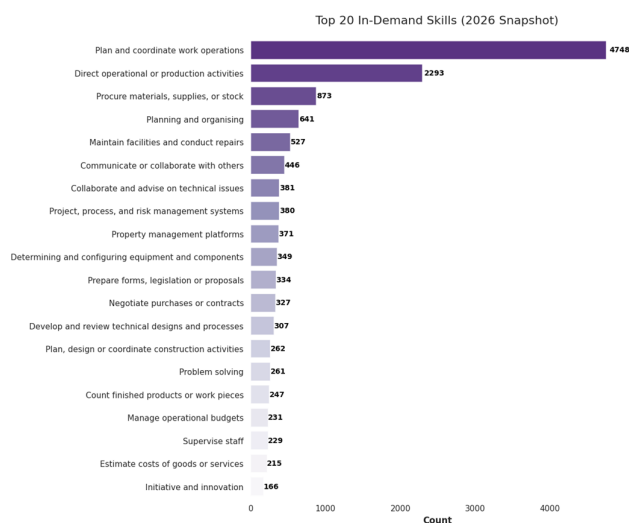


Figure 13. Top 20 most frequently demanded industry skills in the 2026 job advertisement sample.

To further analyse the skills demand, a skills concentration matrix, shown in Figure 14, was generated to identify which specific occupational cohorts are driving the demand for these emerging competencies. The concentration matrix revealed an overlap of occupations and their perceived traditional competencies. Most notably, “Plan and coordinate work operations,” a proficiency traditionally viewed as the exclusive domain of strategic management or technical professionals, emerged as a requirement across the entire sector. It constitutes between 21.6% and 33.0% of the relative skill demand within every single occupational category, including core and specialized trades. Conversely, the matrix also highlights highly targeted, role-specific demands; for example, “Negotiate purchases or contracts” peaks sharply within project support/admin roles (6.9%), while “Maintain facilities and conduct repairs” acts as a primary driver for specialized trades (8.6%). This concentration analysis suggests that employers in the sampled job advertisements increasingly expect operational and trade workers to possess cross-functional coordination and management capabilities alongside their core technical skills.

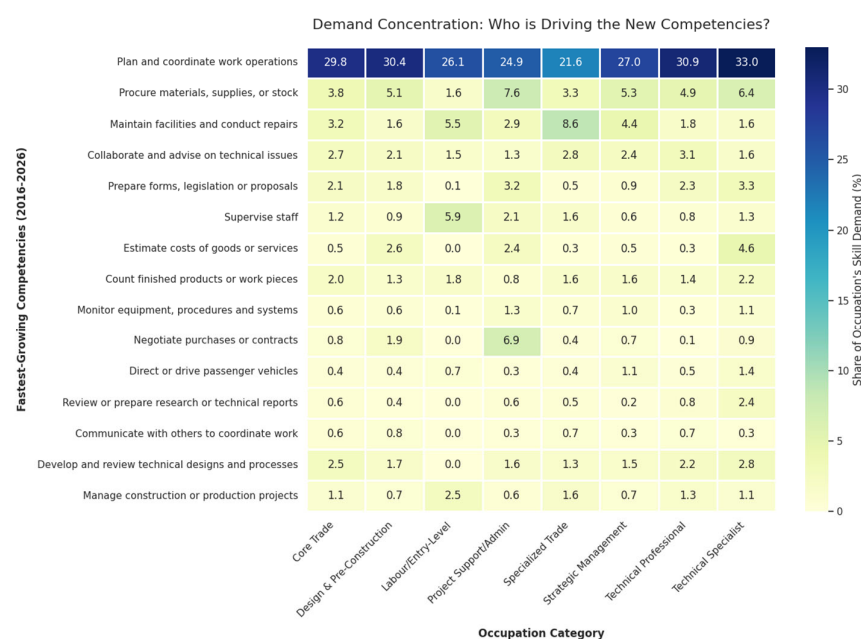


Figure 14. Matrix of industry skills demand against industry occupations from the 2026 job advertisement sample.

Furthermore, the structural network analysis utilizing betweenness centrality helped to understand how these skills interact with each other. As illustrated in Figure 15, “Direct or advise on agricultural matters” (mapping contextually to site preparation) and “Train staff” exhibited the highest betweenness centrality scores (0.037 and 0.036, respectively). This indicates that these proficiencies function as critical nodes bridging otherwise disconnected skill clusters. The emergence of “Train staff” as the prominent bridge skill empirically validates the findings of McLaughlin [39] and Ding et al. [11]. Both studies identify the lack of employer-facilitated in-house training as a critical bottleneck that exacerbates workforce skill shortages. Insufficient training not only limits employee capability, but also restricts their capacity to formally train colleagues. Hence this validates vital bridging skill in this study’s job posting sample.

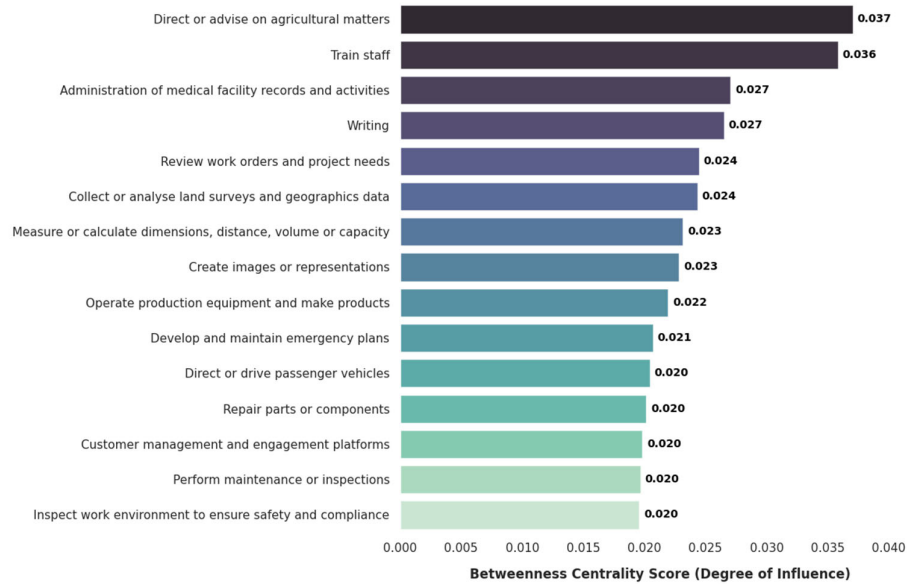


Figure 15. Betweenness centrality for industry skills derived from the 2026 job advertisement sample.

The temporal velocity analysis across the decade revealed shifts in market priorities as shown in Figures 16 and 17. Demand for CC skills within the sampled advertisements presented the sharpest decline (−5.8 percentage points), while ST skills showed the highest growth (+9.5 percentage points). The findings are also in contrast to the literature, which suggests that there is an increased emphasis on soft skills over the past decade [84]. Evans et al. (2024) presented that there has been an increase in demand for interpersonal skills post-pandemic [85]. This has been driven by the demand for communication and collaboration skills [56,85,86]. However, in this sample. The sample in this analysis suggests a transition in labour market dynamics where the operational shortages identified by Jobs and Skills Australia (2023) [33] are likely forcing employers to prioritise specialist technical proficiencies over soft skills in formal job listings.

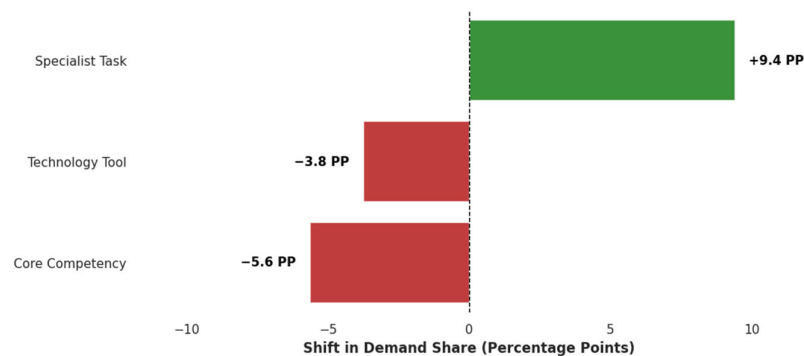


Figure 16. Temporal Velocity in Percentage Points of ASC Categories Between the 2016 and 2026 Job Advertisement Sample.

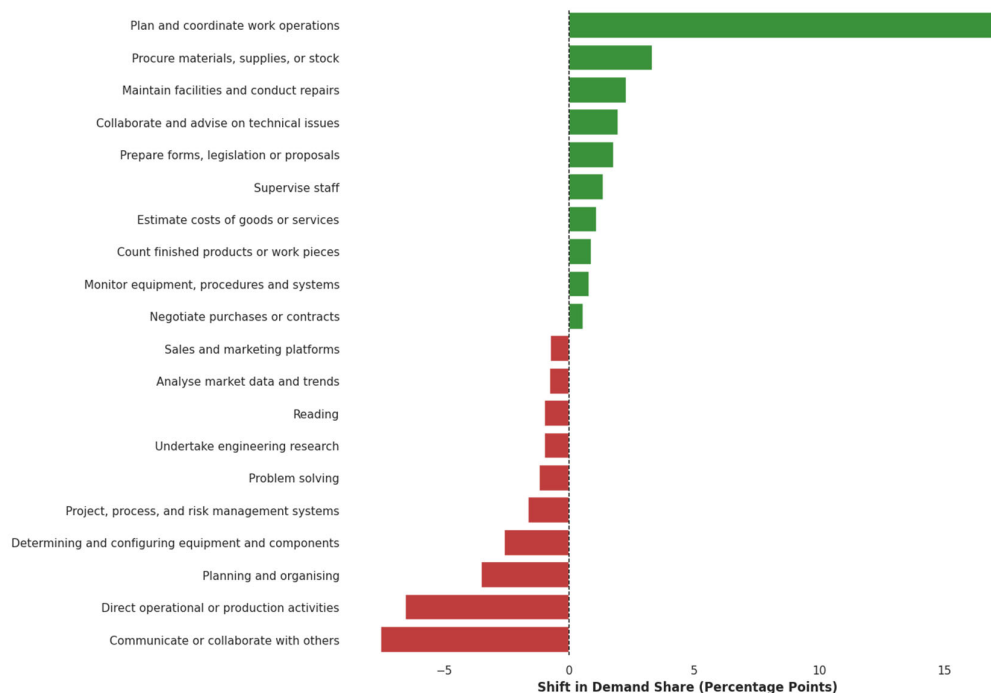


Figure 17. Temporal Velocity in Percentage Points of ASC Skills Between the 2016 and 2026 Job Advertisement Sample.

4.3. Supply-Side Analysis: Educational Provision

Addressing Objective 2, the coverage of skills within official VET data and HE accreditation frameworks was established. Evaluation of the VET data as shown in Figure 18 demonstrated a heavy bias toward ST skills. This constituted nearly 90% of course offerings. Whereas TT and CC skills combined accounted for less than 20% of student offerings. This finding is consistent with characterisations of the VET system as predominantly trade and task-oriented. Callan et al. [41] and Detsimas et al. [38] support this, further adding that VET curriculum is designed to service the immediate, hands-on technical requirements of the trades sector. The granular frequency analysis of the top 20 skills delivered by VET (Figure 19) further illustrates this operational focus; the “use climbing or lifting equipment” emerged as the most frequently taught individual skill, followed by project management and planning.

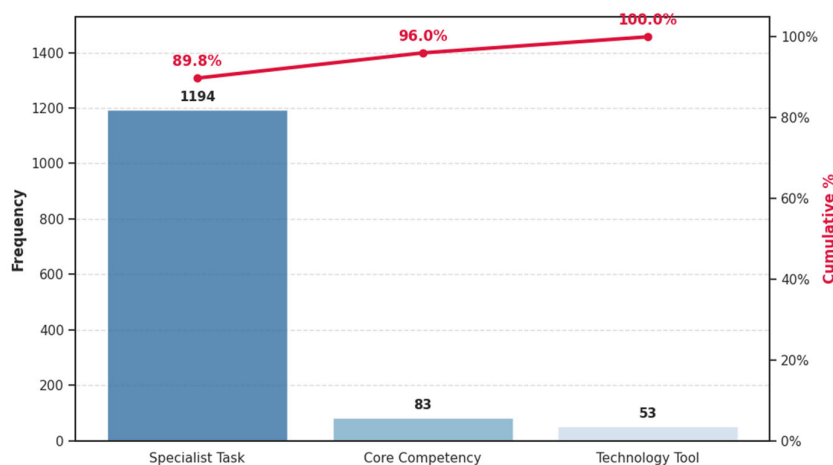


Figure 18. VET Sample Mapped to ASC Categories and Overlaid with a Pareto Chart.

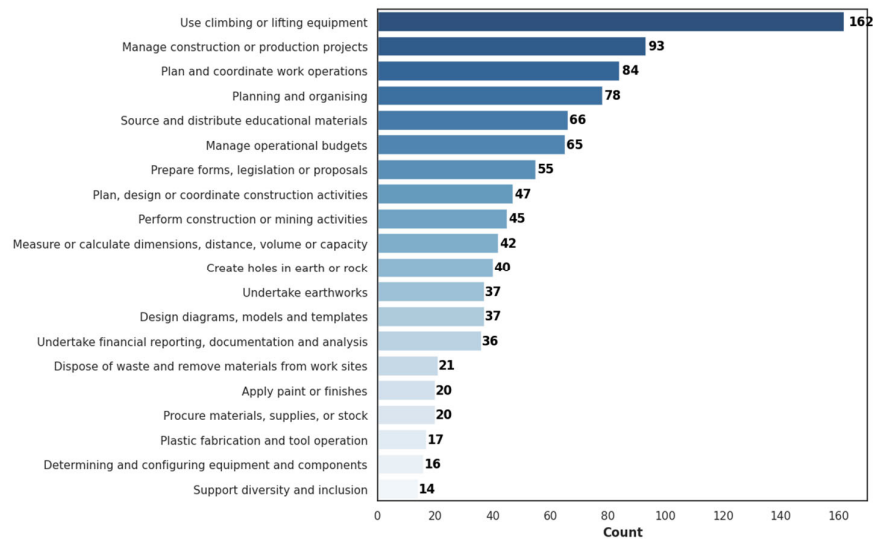


Figure 19. Top 20 Most Repeated Supply Skills from the VET Sample.

Figure 20 revealed a high-level thematic focus similar to VET, with ST skills presented in 87.6% of the mandated requirements. However, the specific types of SS skills being taught in these two sectors could vary. While the VET sector focuses heavily on practical, hands-on execution (e.g., using tools and lifting equipment), HE focuses on cognitive skills (e.g., strategic planning and project management).

This distinction is visualized in the HE top 20 mandated skills (Figure 21). Unlike the VET sector's focus on physical equipment, the HE frameworks are dominated by cognitive and communicative tasks. "Manage construction or production projects" ranks as the highest mandated competency, followed by supply procurement and technical design review. This mathematically confirms that HE institutions are primarily structured to service the strategic management and design phases of the construction lifecycle. However, there is a relatively low presence of explicit TT requirements in the HE frameworks. This supports Papuraj et al.'s [20] assertion that advanced digital tools, such as BIM, remain highly fragmented rather than structurally embedded within core university curricula.

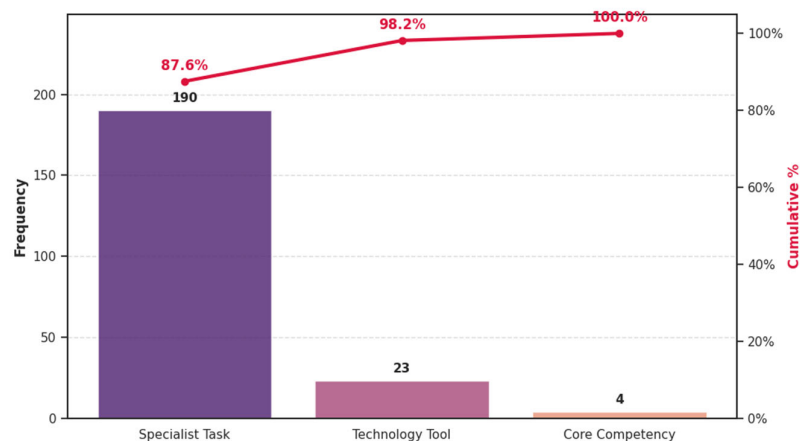


Figure 20. HE Accreditation Sample Mapped to ASC Categories and Overlaid with a Pareto Chart.

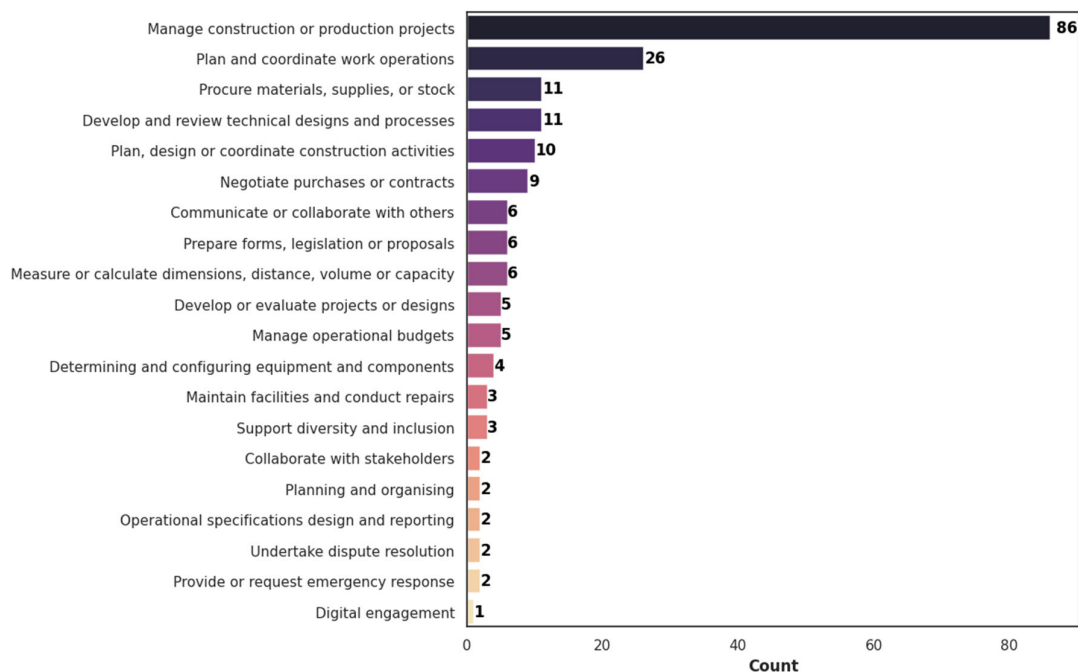


Figure 21. Top 20 Most Repeated Supply Skills from the HE Accreditation Sample.

To facilitate a comparison against the national industry demand, these two distinct educational pathways were aggregated into a weighted Combined Supply Index (72.5% VET, 27.5% HE). The resulting visualization of the total national curriculum categories as shown in Figure 22 demonstrates that ST skills constitute 89.2% of all taught competencies. The combined top 20 weighted competencies shown in Figure 23 captures both the HE-driven “Manage construction or production projects” (#1) and the VET-driven “Use climbing or lifting equipment” (#2) in a single scale.

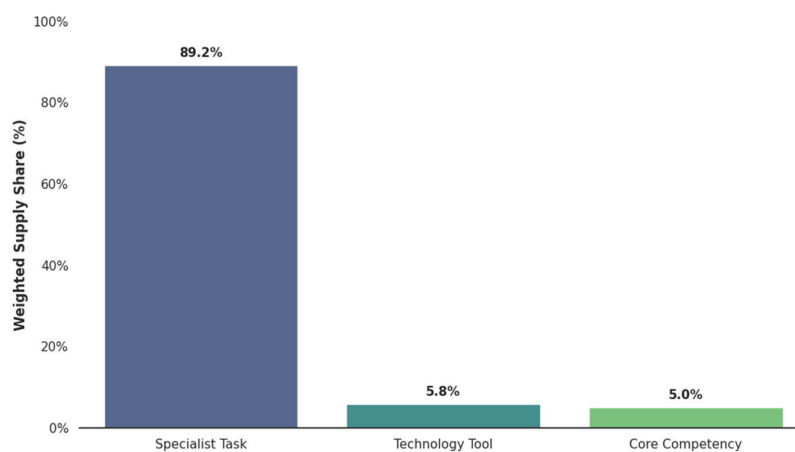


Figure 22. Aggregated VET (72.5%) and HE Accreditation (27.5%) Sample Data Mapped to ASC Categories.

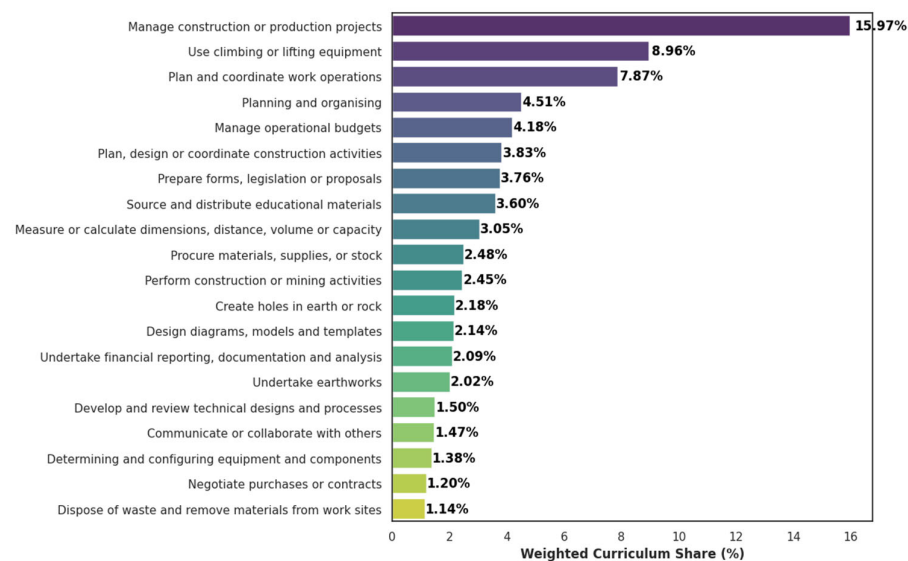


Figure 23. Top 20 Aggregated VET (72.5%) and HE Accreditation (27.5%) Sample Data Mapped to ASC Skills.

The primary contribution of this combined supply vector is methodological. Previous studies characterising educational shortfalls [46,47] frequently relied on employer perceptions or subjective surveys to deduce the ability of graduates as the skills supply. By computationally mapping and aggregating the explicit learning outcomes and accreditation standards, this study provides an objective baseline of how the Australian education sector is structured to cater to the construction industry's skills demand.

4.4. Quantifying the Disparity: Demand vs. Supply Alignment

To achieve Objective 3, the disparity between demand and supply was quantified. To measure the alignment between industry demand and educational supply, cosine similarity was calculated across the three primary skill categories (Figure 24). This analysis revealed that the CC skills group exhibited the highest similarity (0.91) between demand and supply within the sample. This indicates that the specific CC skills taught align relatively well with those demanded, validating Borg and Scott-Young's [56] emphasis on the importance of communication and teamwork curricula. However, given the temporal decline in explicit CC demand as shown in Figure 16, it is likely that soft skills are transitioning to implicit expectations rather than explicit requirements.

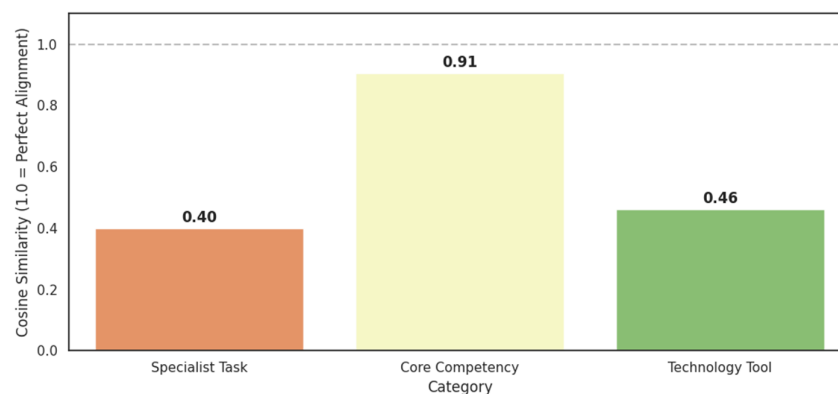


Figure 24. Cosine Similarities of 2026 Job Advertisement Demand and Aggregated VET and HE Accreditation Supply Skills.

ST skill category demonstrated the lowest cosine similarity, indicating a mismatch. This is a concern, as ST skills were the most heavily demanded category by volume in the industry. ST skills were also the fastest growing in terms of demand, with an increase of circa 10 percentage points over the decade, validating a mismatch. This is in line with findings from Oliveros and Vaz-Serra [48] whose systematic literature found a mismatch in construction related hard skills. The education sector dedicates a substantial proportion (90%) of its mapped curriculum to ST skills. However, the specific ST skills represented in the supply data show weak alignment with employer demand in the sampled job advertisements [46,48]. It is important limitation of this study is, a majority of engineering professionals are trained through HE pathways, where individual units of study frequently embed ST skills that the HE accreditation frameworks may not fully

The TT category returned the second highest cosine similarity score (0.46). While it is better aligned than ST skills, it still represents a over 50% mismatch between industry demand and educational supply. This disparity supports existing qualitative literature, which has identified shortages in specific digital proficiencies, most notably in BIM [46,48,87]. Interestingly, the temporal velocity analysis revealed that explicit job advertisement demand for TT skills remained stagnant between 2016 and 2026. Given the sector's push toward Industry 4.0 and digital twin technologies [16], this stagnation suggests that digital proficiencies could be transitioning from being explicitly requested skills to implicit expectations [88].

However, regional policy indicates a potential surge in formal TT requirements. For instance, the Queensland government's recent mandate requiring BIM on all construction projects exceeding \$50 million [89] aligns directly with the spatial concentration of TT demand observed in that state (Figure 11). This regulatory shift indicates that while digital maturity across the broader Australian market remains stagnant, formal demand for TT skills is on an imminent upward trajectory.

Finally, to evaluate the strategic prioritization of specific proficiencies, Spearman's Rank Correlation (ρ) was calculated for both the top 20 skills ($\rho_{\text{top20}} = 0.32$) and the entire dataset ($\rho_{\text{global}} = 0.43$) (Figures 25 and 26). These low coefficients reveal a misalignment in the ranked importance of skills across the demand and supply ecosystems. However, specific areas of alignment do exist; as illustrated in the dumbbell chart (Figure 25), proficiencies such as planning and coordination, materials procurement, construction project management, and teamwork currently demonstrate the strongest alignment between educational supply and industry demand.

Figure 25 shows a dumbbell chart of the top 20 industry demand skills. The space between the circles shows the difference in priorities for each skill in the industry compared to academia. For example, the skills "Plan and coordinate work operations" are closely prioritised in both the industry and academia. However, "Collaborate and advise on technical issues" is prioritised high in the industry but low in academia. Figure 26 is a similar visualisation of this difference in priorities between industry and academia.

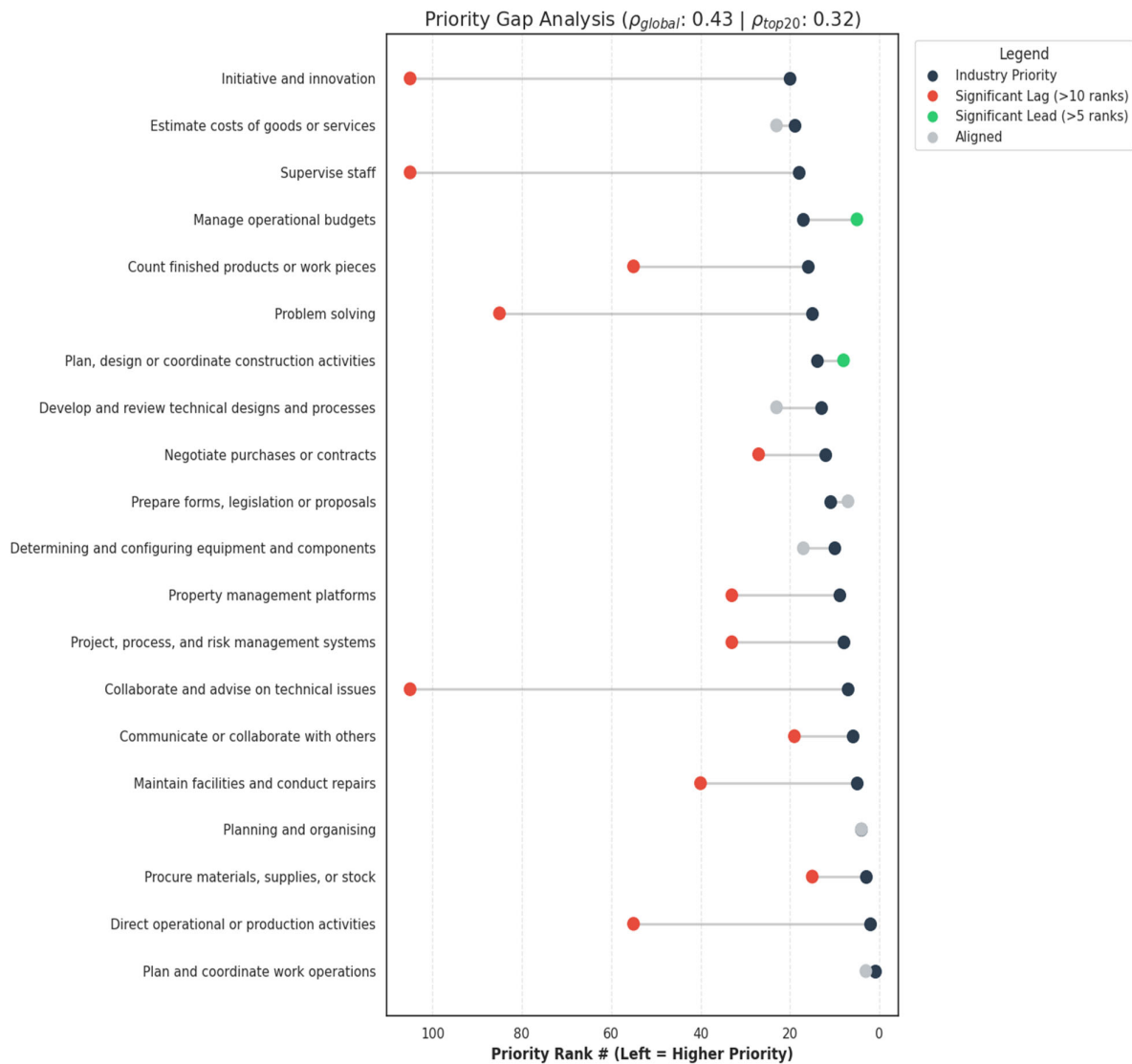


Figure 25. Spearman's Rank Dumbbell Chart of 2026 Job Advertisement Demand and Aggregated VET and HE Accreditation Supply Skills.



Figure 26. Spearman's Rank Bump Chart of 2026 Job Advertisement Demand and Aggregated VET and HE Accreditation Supply Skills. The red lines show skills demand in the sample job postings data that have a lower priority ranking in the curriculum while the green lines show skills that have a higher priority ranking in the curriculum.

Further to the above, the directional skills gap was computed on the top 20 industry demanded skills. As shown in Figure 27, many of the top 20 industry demanded skills show a positive directional demand-supply index. This means that the sampled curriculum is not giving enough importance and curriculum space to the skills that the industry needs the most.

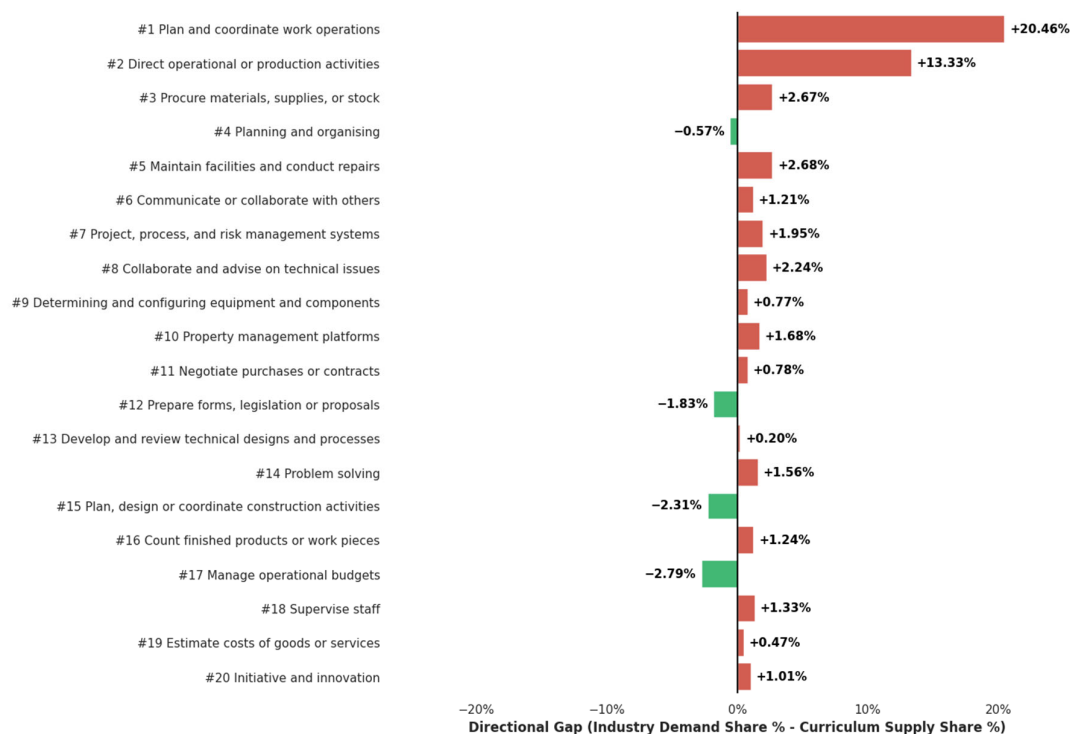


Figure 27. Directional skills gap computed using the directional Demand–Supply Gap Index for the top 20 industry skill demands.

The largest positive gap was observed for “Plan and coordinate work operations” (+20.40%), followed by “Direct operational or production activities” (+13.36%). These two skills account for the most pronounced directional shortages within the top twenty industry-demanded skills, indicating that employer demand is concentrated around operational coordination, production direction and work-planning capabilities that are not proportionally reflected in the mapped curriculum supply.

Smaller but still positive gaps were also observed for “Procure materials, supplies, or stock” (+2.71%), “Maintain facilities and conduct repairs” (+2.54%), “Collaborate and advise on technical issues” (+2.27%), “Project, process, and risk management systems” (+1.83%) and “Property management platforms” (+1.78%). These results suggest that the curriculum supply does not only diverge from industry demand at the aggregate category level, but also at the level of specific applied workplace capabilities.

Conversely, few skills showed negative directional gaps, where curriculum representation exceeded observed employer demand. These included “Manage operational budgets” (−2.80%), “Plan, design or coordinate construction activities” (−2.27%), “Prepare forms, legislation or proposals” (−1.77%), and “Planning and organising” (−0.69%). These negative values do not necessarily indicate that these skills are unimportant. Rather, they suggest that these capabilities are more strongly represented in the curriculum data than in the sampled job advertisement demand signals.

Overall, the directional gap results show that the strongest misalignment is not simply between broad skill categories, but between the specific operational and coordination skills prioritised by employers and the skills most visibly represented in education and accreditation documents.

4.5. Evidence-Based Recommendations

Addressing Objective 4, the computational analyses conducted in this study successfully identified specific skill mismatches. Recognizing the sample-based nature of this dataset, the following targeted interventions are proposed for consideration:

1. Realignment of Specialist Task Curriculum:

The weighted Combined Supply Index (Figures 22 and 23) revealed that the education sector dedicates 89.2% of its curriculum content to ST skills, yet the cosine similarity analysis (Figure 24) returned a severe mismatch score of 0.40 for this category. This finding suggests that, within the sample, the observed skills gap is not only a matter of education volume, but also a matter of alignment between the specific Specialist Task competencies taught and those demanded by employers. For example, while the VET supply frequency analysis (Figure 19) shows “Use climbing or lifting equipment” as the most heavily taught skill, the industry demand velocity analysis (Figure 17) shows “Plan and coordinate work operations” as the fastest-growing employer requirement. To resolve this, educational bodies may use these results as a diagnostic tool for curriculum review, alongside academic judgment, accreditation requirements, assessment design, student learning outcomes, and industry consultation.

2. Elevating Bridge Skills to Core Requirements

The structural network analysis, utilising betweenness centrality (Figure 15), mathematically identified “Direct or advise on agricultural matters” (which maps contextually to site preparation and environmental compliance; 0.037) and “Train staff” (0.036) as the highest-scoring bridging nodes. The value of this network analysis is that it moves beyond simple frequency counts to show how certain competencies bridge otherwise-disparate skill clusters in an otherwise multidisciplinary construction industry. Neither of these top bridging skills appeared in the top 20 most in-demand skills in the job posting sample. This validates the qualitative findings of McLaughlin (2022), who cited a lack of in-house training as a primary driver of low productivity [39]. Given their structural importance in the network, it is advisable for academia and industry to elevate specific mentoring, staff-training and site-preparation compliance modules from optional electives to mandatory core requirements. This is likely to reduce cross-disciplinary communication bottlenecks on site.

3. Integration of Technology Tools into Specialist Task Curriculum

The cosine similarity analysis (Figure 24) showed that the TT category had a poor alignment score of 0.46 between the sampled 2026 job postings and the aggregated VET and HE accreditation data. Furthermore, the temporal velocity analysis (Figure 16) revealed that the demand in job advertisements for general TT skills remained stagnant over the decade. This data-driven finding validates the literature by Papuraj et al. (2025) and Kehoe et al. (2026), who argued that digital education in construction is currently fragmented [20,87]. The value of this finding is that it quantitatively suggests digital fluency is transitioning into an implicit expectation rather than an explicitly advertised skill. Consequently, rather than offering generic digital literacy or isolated IT electives, HE and VET providers should pivot towards embedding specific, industry-standard software such as BIM and specialised project management platforms (Figure 13) directly into core ST modules. This would likely better mirror the contextual reality of how these specific tools are utilised on modern construction sites.

4. Adopt Computation-Driven Accreditation

Spearman’s rank correlation analysis for the top 20 skills ($\rho_{\text{top20}} = 0.32$) mathematically demonstrated that the sampled academia data did not prioritise skills in a similar way to the sampled job posting data. This is further visualised in Figure 25 and Figure 26. The literature calls for highly frequent skills gap analyses to keep pace with the rapidly

evolving sector [23,25]. Methodologically, this study contributes more than an aggregate similarity comparison between industry and education. First, it integrates job advertisement data, VET unit data, and HE accreditation standards into a common ASC-based taxonomy, enabling like-for-like comparison across otherwise fragmented demand and supply sources. Second, it combines cosine similarity with Spearman's rank correlation and a directional demand–supply gap index, allowing the analysis to distinguish between overall semantic alignment, priority alignment, and directional undersupply. Third, the partial ground-truth validation test provides an empirical check on the reliability of the automated SBERT mapping. This combination of methods addresses a key limitation in previous construction skills-gap research, which has often relied on small-scale interviews, surveys, or manual thematic coding.

5. Conclusions

The Australian construction industry is presently witnessing a productivity challenges, which is further exacerbated by the scarcity of skilled workers. In the past, the quantification of the skills gap was carried out through subjective surveys, or localised expert interviews. The novelty of this research lies in the fact that it bridges this gap by applying an objective natural language processing (NLP)-based approach to the chosen context and its overall methodology. By using the SBERT model, the current research successfully avoided the inherent observation biases of the small-scale curriculum-gap analyses.

The study assesses the textual alignment between documented curriculum supply and observed industry demand. The major contributions and results of this study, which address the four objectives, are as follows. In achieving the first objective, the analysis of the 3468 sampled job advertisements identified that the industry demand was dominated by the need for specialist tasks (STs), as well as the rapidly increasing need for operational coordination. The sample identified that the demand for core competencies (CCs) had diminished over the last ten years. In achieving the second objective, the synthesized VET unit data and Higher Education accreditation standards were combined into a weighted supply vector (72.5% VET, 27.5% HE), which showed that nearly 90% of the Australian education sector's combined curriculum consisted of ST skills. In achieving the third objective, the analysis identified the gap between the supply and demand of the sample. The large volume of ST skills supplied was found to have a poor cosine similarity score of 0.40. In addition, Spearman's rank analysis ($\rho_{\text{top20}} = 0.32$) revealed poor priority alignment between the sampled academic curricula and job posting data, suggesting that the curricula did not prioritise skills in the same order as employers. Finally, with regards to Objective 4, the study identified specific areas of intervention, namely the integration of specific Technology Tools (TT) into core modules and the elevation of bridge skills (e.g., staff training and site preparation) to mandatory requirements.

The implication of this study is that curriculum–industry alignment is one measurable component of the broader construction skills challenge. The results suggest that education volume alone is insufficient if the specific skills prioritised in curricula do not align with changing employer demand. This does not discount other contributors to skills shortages, including wages, working conditions, labour mobility, demographic change, firm-level training investment, and project delivery conditions. This study has provided educational policy makers, universities, and VET institutions with a scalable methodology for agile syllabus auditing, ensuring that skills supplied by academia do not lag behind those required by construction industry stakeholders.

This study also recognises some limitations. This methodology analyses textual signals and structural frameworks rather than observational workplace practice or classroom delivery. Therefore, these findings represent indicative evidence of pedagogical align-

ment patterns, highlighting potential factors rather than directly measuring individual graduate competence. Firstly, it is recognised that job advertisement data only capture the formal labour market. Underrepresented demographics often rely on informal networks to gain employment. This results in some skill vectors not being fully captured. Secondly, to determine the HE supply, this research had to rely on professional accreditation frameworks. Whilst the accreditation frameworks for HE provided minimum course requirements, this information was not as detailed as the VET data. This resulted in some skills not being fully captured in the supply vectors. Thirdly, this research had to rely on the standard JobBERT models. The more optimal JobSpanBERT was not available to the public domain, and so skills extraction was not as effective as it could have been. Lastly, the assessment of the skill gap relied on metrics such as cosine similarity and Spearman's rank correlation coefficient. This research did not have the ability to statistically validate using methods such as ANOVA and t-test methods, and so the skill gaps identified must be seen as indicative trends rather than definitive metrics.

To address these limitations, future research should apply this data-driven approach to a particular sector, like civil engineering, and that a statistical validation be carried out. In addition, future studies can be enhanced by developing a model for automated extraction of information from individual university course handbooks. In addition, future research should also explore alternative machine learning architectures such as BERT or TF-IDF to compare the accuracy of SBERT as the semantic mapping tool for the skills taxonomy.

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Abbreviations

The following abbreviations are used in this manuscript:

ST	Specialist tasks
CC	Core competencies
TT	Technology tasks
ASC	Australian Skills Classification
HE	Higher education
VET	Vocational education training
ANZSCO	Australian and New Zealand Standard Classification of Occupations

ANZSIC Australian and New Zealand Standard Industrial Classification

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