YRKESHÖGSKOLAN NOVIA

Computational Skills for Classical Engineering Disciplines

Outlining key components of a curriculum that integrates computational thinking and skills for engineering disciplines in Finland.

Antonio Romero

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Author: Antonio Romero
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Supervisor(s): Johan Degerlund, Novia UAS

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Abstract

This thesis examined the integration of computational skills into classical engineering education to address the digitalisation challenges faced by the Architecture, Engineering and Construction (AEC) industry and aimed to determine whether incorporating dedicated computational courses could bridge the skills gap inherent in traditional curricula to prepare future engineering graduates.

A mixed method research, combining a comprehensive literature review, surveys, interviews with industry professionals and academic leaders, and guided practical lectures with undergraduate engineering students. The literature review was based on four pillars. The AEC digitalisation process, the digital skills gap in the industry, the current and future state of engineering education and lastly, from a legal and socio-political point of view. The research investigated current Finnish engineering curricula and compared them with the curricula from other international universities. The research revealed a significant deficiency in dedicated computational training in Civil and Structural engineering faculties and that early integration of computational thinking may enhance readiness for industrial demands. Recommendations are provided for curriculum redesign, fostering investment in faculty development and collaboration between academia, industry, and policymakers.

Language: English
Key Words: computational thinking, digitalisation, engineering education, higher education

"Knowledge is power. Information is liberating. Education is the premise of progress, in every society, in every family." – Kofi Annan

A Nélida

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Abbreviations

AAD	Algorithmic Assisted Design
ADT	Advanced Digital Technologies
AR	Augmented Reality
BIM	Building Information Modelling
CAVE	Computer Assisted Virtual/Visualisation Environment
CD	Computational Design
DT	Digital Twin
FEM	Finite Element Method
IoT	Internet of Things
PPS	Purchasing Power Standards
RAG	Retrieval Augmented Generation
RDI	Research, Development and Innovation
ROI	Return On Investment
RPA	Robotic Process Automation
SME	Small and Medium Enterprises
UAS	University of Applied Science
VDC	Virtual Design and Construction
VR	Virtual Reality

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1 Introduction

The EU Procurement Directive 2014/24/EU established the promotion of a BIM mandate for the procurement of public projects, jumpstarting the need for digitalisation in the Architecture, Engineering, and Construction (AEC) industry. However, studies have shown the AEC industry's digitalisation level lags significantly behind that of other industries. The transition to a digitalised AEC industry faces multiple challenges, including high costs, lack of investment, legal issues, standardisation problems, and varying levels of stakeholder engagement. Additionally, the industry has a significant shortage of digitally skilled professionals and a lack of digital culture. This thesis aims to address and explore this issue.

Upskilling employees to understand the digital nature of the engineering process is expensive both in time and money. AEC firms are often unsure of the cost-benefit of upskilling and training employees. It can be argued that higher-level management, who must approve this investment, and the employees see digitalisation merely as a "new tool" rather than a "new way of thinking." Digitalisation is considered as foreign to the industry and, in general terms, lacks a computational approach to problem-solving because they "are not an IT company." Digitalisation is a service that can be bought, not a cultural shift from within, yet digitalisation is inevitable. Part of the resistance to cultural change stems from the fact that, during their formative years, technicians, core discipline engineers (structural, civil, geotechnical, etc.), and their managers and directors are barely exposed, if at all, to the core competencies needed to manage data. Core discipline engineering students continue to learn the same topics taught since the formalisation of engineering schools. Supported by legal mandates that require, for example, that a structural engineering student learns statics, engineering schools and universities focus on these traditional topics while neglecting computational skills. In an industry desperately in need of higher levels of efficiency, neglecting computational training is short-sighted.

Furthermore, for engineers themselves, when the solution to digitalisation is simply to buy a license or service, they risk becoming mere technicians, users of "black-box" tools they do not understand making them vulnerable to obsolescence, as they lose the critical understanding needed to innovate and adapt. Engineers risk being side-lined in an increasingly rapidly changing digital world by relying on tools that they cannot fully understand or control. The danger is clear: Without embracing and mastering digital competencies, engineers, as professionals, face the threat of becoming outdated and irrelevant in their field, falling into a state of digital illiteracy that makes them vulnerable to manipulation and incapable of critical thinking and informed engagement.

While it is true that educational and business initiatives exist to "bridge the gap", they are limited at best. In general, the required skills to create, manipulate, and optimise data are outsourced to computer science professionals, programmers, or IT specialists, and occasionally to a new breed of engineers called “computational designers” who, out of necessity, fill the void. More importantly, “core engineering” programs do not cover the skills needed to digitalise the industry.

To use an engineer’s idiom, we are "building the house from the roof." Regulation demands digitalisation, yet those expected to carry it out lack the fundamental competencies required.

1.1 Objectives

The arguments presented above, if right, underscore the need for a new kind of specialisation or the inclusion of computer science courses in classical engineering degrees, to equip future engineers with critical digital competencies that go beyond basic computer usage. The aim of this thesis is to explore and confirm this need by addressing the following questions:

- According to students, practitioners, and higher education entities, do computational courses have a place in “classic engineering” degrees?
- What are the key components and topics of those courses?
- Do they work in practice?

To answer these questions, the research conducted employed a mixed-methods approach. Firstly, a through a thorough review of academic literature to analyse available insights. The review was structured on four pillars related to AEC digitalisation and engineering education: The digitalisation process, the digital skills gap in the industry, the current and future state of education, and finally, legal, and socio-political considerations. This was to offset the potentially limited access for collaboration in the other methods. Secondly, data collected through questionnaires, formal targeted interviews, and informal, of-the-record conversations with various stakeholders, including current engineering students, industry professionals and academic leaders, measured perceptions and expectations regarding the integration of computation in traditional engineering education. Lastly, a series of guided practical lectures were conducted with current engineering undergraduates to expose them to computational thinking. The sessions aimed to find whether early exposure facilitates a natural bridge between the physical and digital world and if the recommendations found in the literature works.

Through this research, the thesis seeks to determine and establish a framework for future implementation, aspiring to ensure that future engineers are proficient in traditional engineering practices and also are equipped with the digital skills necessary to remain competitive and relevant in the rapidly evolving technological landscape.

2 The state of digitalisation of the AEC industry

The digitalisation of the AEC industry presents a paradox. On the one hand, it offers immense potential. On the other, it confronts persistent challenges because of engrained culture and ways of work. Despite the availability of transformative technologies, including BIM, AI, IoT and others, their adoption throughout the sector is still inconsistent and limited. The industry’s fragmented nature, marked by project-specific processes, intense manual work, and the short-term nature of projects, hinders the seamless integration of digital tools and workflows, impeding the accumulation of institutional knowledge needed for sustained innovation. This state aggravated by cultural resistance. Many professionals view digitalisation less as a strategic necessity, and more as a threat to well-known traditional workflows. Also, the high costs associated with acquiring and implementing advanced technologies deter SMEs, which comprise a substantial portion of the AEC industry landscape, from fully participating in the digital transformation.

More so, external pressures such as the COVID-19 pandemic and heightened sustainability goals have accentuated the urgent need to adopt digital solutions to address operational inefficiencies and environmental concerns. Some progress has indeed materialised. The deployment of remote and web-first collaboration tools, a growing interest in open standards, resource optimisation strategies and an incipient computational approach to problem-solving have delivered modest progress. However, the industry's slow overall pace of digitalisation highlights a more relevant issue: an industry-wide gap in digital competencies among practitioners and a lack of cohesive frameworks to support innovation.

A coordinated effort involving policy interventions, educational reforms, and leadership commitments is essential to bridge this gap. Only by rethinking its approach to digitalisation and building it from the foundations, can the industry embrace these technologies not as supplementary “nice to have tools” but as integral components of its evolution towards greater productivity, collaboration, and sustainability. Lagging digital adoption

When compared to other industries such, as manufacturing or retail, the AEC industry has been slow to adopt digital technologies (Mckinsey, 2023) (Roland Berger, 2016), with only a handful of AEC companies making full use of advanced digital tools for planning and execution as an example. The issue is even more acute when looking at SMEs that normally lack economical and workforce resources, to implement these changes. Research and development in the AEC industry also lag compared to other sectors. This greatly limits the capacity for innovation and technology adoption (Brozovsky;Labonnote;& Vigren, 2024).

The lack of significant and comprehensive training and education, and the skill gap noted among the workforce, both in blue and white-collared employees, leaves the industry ill-equipped to adequately take advantage of the digital transformation (Chen X. C.-R., 2024).

Despite its critical societal role, the AEC's digital adoption lags due to entrenched traditional practices (European Construction Sector Observatory, 2021) (Stolton, 2019) aggravating the current situation. A comparison of studies from 2016 to 2024 did see progress, yet modest at best. A good example of this is BIM. Long present in the industry, it still is a wagon rather than the locomotive in AEC engineering processes. While BIM and GIS are recognised as transformative tools for project development, management, visualisation, and decision-making their adoption is limited, and many firms still struggle to implement BIM effectively. Even more so in complex projects, due to skill gaps and financial constraints. (Manzoor, 2021) (Brozovsky;Labonnote;& Vigren, 2024). Robotics, AI, IoT and sensor technologies are still in their infancy, and implementation is limited and constrained by high costs, interoperability complexities and other factors hampering their full potential. Again, the underutilisation of emerging technologies in the industry should not come as a surprise.

2.1 Limited industry training

Recent studies show a clear disparity between the skills required to implement digital technologies effectively and the actual competencies of current industry professionals (Chen, ym., 2023), with many firms not investing adequately in upskilling their workforce. Digital training perceived as costly and time-intensive, with uncertain returns on investment, but the need for learning and reskilling exists. The European Commission, in its "Supporting Digitalisation of the Construction Sector and SMEs" report (European Commission, 2019), clearly identified lack of training and expertise as two of the ten most acute gaps identified for action and recommended new experts to be trained in "both methodological skills (mathematics, computation, building-physics, manufacturing, structural mechanics etc.) and technological skills (programming languages, software applications etc.)” citing the “need to be integrated into the curriculum of higher education for construction disciplines” (European Commission, 2019) .

Figure 2-1 Skill gaps in the AEC industry (European Commission, 2019) .

Again, this is particularly acute in small and medium businesses and in contractors, quantity surveyors, supply chain companies and other key players, blue-collared included, who may have had only limited exposure to advanced digital tools and training opportunities (Brozovsky;Labonnote;& Vigren, 2024). The lack of structured, truly active training programs within organisations, be that by missing altogether or by just existing as a nominal placeholder of future action, creates barriers to adoption and resistance. This leads, at best, to superficial adoption with employees lacking confidence and ability to work with them, and at worse with underutilised technologies and missed opportunities. In the case of large-size AEC organisations where access to training is nominally “provided,” the process often is half-hearted and passive, leaving employees to engage in self-learning. This solution is not producing the desired results. Without comprehensive, targeted support, this “figurative approach” undermines the potential for skill development and limits the organisation’s capability to benefit from digitalisation initiatives (Schildt, 2022). Thus, addressing this gap is essential to fully harnessing the industry's potential through a digital transformation.

2.2 Resistance, slow adoption, and flat productivity

The industry heavily depends on labour-intensive manual processes and fragmented workflows that replicate work done on paper onto a screen. Consequently, productivity growth in the AEC industry has been underwhelming. The limited adoption of and limited capabilities in computation, automation and other digital processes have perpetuated inefficiencies and missed opportunities for productivity gains[1]. A decades-old trend that

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[1] This was the subject of a discussion during the AI-in-AEC 2025 conference held in Helsinki (Finland), where the CEO of a major Engineering firm argued that consistently advances in productivity had been passed down as discounts to the clients who have benefited from those without it being counted as productivity gains, also mentioning examples like the prefabricated modular construction that would appear under other industry in the statistics, leading to a deviated statistical calculation.

stagnates the whole AEC industry (Brozovsky;Labonnote;& Vigren, 2024). A significant part of AEC professionals view digitalisation as disruptive to traditional processes and really struggle to implement them in their daily work, reluctant to embrace a digital approach as identified by (Chen, ym., 2023) (Hu, 2023) (Manzoor, 2021).

When stakeholders see digital tools as supplementary rather than foundational, it leads to superficial adoption rather than full integration in business processes (Bosch-Sijtsema;Claeson-Jonsson;Johansson;& Roupe, 2021). In these cases, stakeholders perceive the digitalisation of engineering and business processes as foreign to the industry. The lack of digital culture and innovation mindset among industry leaders significantly worsens the challenges of digital transformation. Without a clear vision and commitment from leadership, organisations struggle to foster a culture that embraces innovation and learning. Thus, when leaders fail to champion digital transformation and reskilling of employees, they create environments where innovation is undervalued, leaving unmotivated employees ill-equipped to do better work. On the other hand, organisations that actively cultivate a culture of continuous learning, rewards, and innovation and integrate digital transformation into the core of their strategy will dominate. (Bosch-Sijtsema;Claeson-Jonsson;Johansson;& Roupe, 2021).

3 The benefits of digitalisation

When properly implemented, the integration of digital technologies and processes results in transformative benefits. They drive efficiency and improve sustainability and productivity goals across the whole sector. These tools enhance collaboration, real-time data sharing and decision-making. They enable better project coordination and result in an overall benefit for all stakeholders despite other perceived costs. These technologies support the industry by optimising resource management, reducing waste and advancing design decisions in all fields of application from energy efficiency to circularity. Fundamentally digitalisation enhances the quality of engineering products, better aligning them with the unique challenges they might face, societal, environmental, and business alike. As long as the industry and the individual stakeholders embrace the principles of "Construction 4.0," digitalisation will enable integrated, sustainable and efficient projects despite other challenges (Nabizadeh Rafsanjani & Hossein Nabizadeh, 2023) (Chen;Huang;Liu;Osmani;& Demian, 2022).

Digital technologies fundamentally enhance the quality and effectiveness of engineering outcomes by allowing professionals to create data-driven insights, based on advanced simulations, real-time monitoring, and optimised designs. Digital first solutions can be tailored to specific project requirements and are better aligned with the project's unique challenges and opportunities, ultimately delivering better value to stakeholders.

3.1 Enhanced efficiency and collaboration

The adoption of digital technologies like BIM, GIS, cloud platforms, and the growing interest in open file formats, have enhanced visualisation, coordination, and interoperability among stakeholders. These tools enable continuous information sharing, facilitating design, construction, and operational phases (Chen X. C.-R., 2024) (Brozovsky;Labonnote;& Vigren, 2024). They enhance collaboration, reduce error, and improve decision-making through integrated project models (Nabizadeh Rafsanjani & Hossein Nabizadeh, 2023). BIM functions as the central key technology for collaboration, providing a unique source of truth. Stakeholders can then work together on shared models, reducing miscommunications, inconsistencies, and discrepancies during the project life-cycle. BIM enables near real-time updates to designs and plans and ensures stakeholders alignment with the latest project requirements, from architect to contractor. Research indicates that, when properly implemented, BIM's collaborative features lead to improved decision-making and reduced rework, as project teams can identify and resolve potential conflicts earlier during the planning phase. (Bolpagni;Ribeiro;D.;& Gavina, 2024) (Manzoor, 2021) (Brozovsky;Labonnote;& Vigren, 2024)

Cloud platforms and IoT strengthen collaboration by enabling seamless data sharing. Using available “cloud” technologies such as web-based repositories, project information is accessible to all project members regardless of location, enabling faster, better-informed decisions. This connectivity allows for collaborative project delivery methods, which rely on close coordination among stakeholders; for example, IoT sensors monitor construction site conditions, sharing real-time project evolution. Integrated project databases help teams monitor progress, detect deviations from schedules and budgets and facilitate early corrective actions where and when needed (Romero, Automated BCF Data Extraction For BIM QC Communication, 2019), providing teams with actionable insights in real-time. (Lavikka;Kallio;Casey;& Airaksinen, 2018) (Chen X. C.-R., 2024) (Brozovsky;Labonnote;& Vigren, 2024) (Manzoor, 2021). In other words, these technologies enable a transparent and communicative project environment, bridging the traditional silos of the AEC industry and leading to more cohesive project execution while delivering enhanced value to clients. (Lavikka;Kallio;Casey;& Airaksinen, 2018)

As the digital transformation continues in the AEC sector, integration of cloud technologies and software will be critical for achieving higher levels of efficiency, collaboration, and project success.

3.2 Enhanced sustainability

The digitalisation of the AEC industry will have clear, positive impacts in terms of sustainability, circularity, and carbon footprint reduction. The adoption of BIM and GIS applications and the automation and digitalisation of processes will allow for precise calculations in material and energy requirements and will help reduce carbon footprints during the planning and life-cycle of projects. Waste will be minimised, and construction processes’ side-effects will be reduced. The potential of applications such as 3D printing, while still not proven, could help by producing and using only the strictly required components (Chen;Huang;Liu;Osmani;& Demian, 2022) (European Construction Sector Observatory, 2021).

Increased energy efficiency in buildings is one of the biggest “opportunities for improvement” arising from the digitalisation of the industry. Digital twins and simulation of energy generation and consumption processes will help design more energy-efficient buildings. Smart sensors and IoT devices will allow real-time monitoring of consumption patterns, optimisation of energy use, early fault detection and fine-tuning of operations and performance to maximise efficiency. (Nabizadeh Rafsanjani & Hossein Nabizadeh, 2023) (Chen X. C.-R., 2024) (Bolpagni;Ribeiro;D.;& Gavina, 2024).

The integration of digital tools facilitates life-cycle assessment and optimisation in construction, allows for material monitoring during the lifetime of the building, sustainable material selection and reduced environmental impact by ensuring resources are utilised more effectively throughout the building's life-cycle (Nabizadeh Rafsanjani & Hossein Nabizadeh, 2023).

AI-powered design tools could analyse project parameters to produce energy-efficient and resource-optimised designs. Modular construction processes, supported by BIM, can minimise on-site waste and allow for more sustainable assembly practices. This ensures resources are used effectively, reducing the environmental footprints of projects (Chen;Huang;Liu;Osmani;& Demian, 2022) (European Construction Sector Observatory, 2021) (Hu, 2023).

Digitalisation will also support urban sustainability integrating with “smart city” initiatives. BIM and IoT optimise urban systems, including water, energy, and waste management. Furthermore, digital tools facilitate the inclusion of renewable energy systems like solar and wind into urban and building designs, ensuring long-term environmental sustainability (Chen;Huang;Liu;Osmani;& Demian, 2022) (Nabizadeh Rafsanjani & Hossein Nabizadeh, 2023).

Digital technologies contribute to the reduction of carbon emissions by streamlining construction processes,. Optimised planning, reduced machinery idle time, and data-driven carbon monitoring could help stakeholders identify and reduce emission targets. These innovations will make the construction phase more environmentally friendly while supporting broader climate goals (European Construction Sector Observatory, 2021) (Chen;Huang;Liu;Osmani;& Demian, 2022).

Digitalisation fosters a “cradle to grave to cradle again” circular economy in the AEC industry by promoting material traceability and reuse. Digital building logbooks and material “passports” enable stakeholders to track materials, facilitating recycling and repurposing. BIM-based designs can further incorporate circular principles by recommending low-impact, recyclable materials, enhancing sustainability at every stage of construction (European Construction Sector Observatory, 2021) (Chen;Huang;Liu;Osmani;& Demian, 2022).

Lastly, digital technologies will improve social sustainability by enhancing the quality of life for building occupants and ensuring adherence to sustainability regulations. Smart sensors in buildings could monitor air quality, lighting, vibration, and noise levels, creating healthier indoor environments. More importantly, digital tools ensure construction practices are transparent, regulatory compliant, and environmentally responsible, helping communities and ecosystems alike (Chen X. C.-R., 2024).

3.3 Enhanced productivity

Digitalisation is poised to help with the productivity increase the AEC industry badly needs. When properly digitalised, digital business and engineering processes help reduce delays and inefficiencies and allow for better results. Recent advancements in technologies such as robotics, automation, digital project management tools, and immersive visualisation platforms such as AR and VR, and CAVE could potentially help achieve significant efficiency gains across all project stages. (Manzoor, 2021) (Brozovsky;Labonnote;& Vigren, 2024)

Robotics, and in particular automation, have the potential to be drivers of productivity. Robots, for example, perform repetitive and manual labour-intensive work with greater precision and consistency. In hazardous tasks, robots will help reduce sinistrality and, in general, reduce employee risks. For instance, automated bricklaying and prefabrication technologies allow for faster project delivery and reduce the risk of errors and employee injuries, ensuring safer working environments and addressing safety issues of traditional construction methods. Some of these systems, partially or totally automated, even when representing a small fraction of the total work done on-site, are already in full use (Manzoor, 2021) (Brozovsky;Labonnote;& Vigren, 2024).

Figure 3-1 Vanku B.V.Tiger-Stone paving machine

In terms of automation, fully digital business-integrated project management tools and ERP software play a critical role in improving oversight, resource allocation and project success. When powered by large data predictive analytics and well-known processes, digital dashboards enable precise tracking of project progress, budgets, and other resources. They provide project managers and other stakeholders with insights that help anticipate project challenges, mitigate delays and cost overruns, ensuring that projects remain on schedule and within budget (Roland Berger, 2016) (Chen X. C.-R., 2024) (Romero, Automated BCF Data Extraction For BIM QC Communication, 2019). RPA software allows for automated handling of administrative tasks like document management and other procurement processes typical to any business. Often, these processes require high-volume data entry tasks and report generation, and they consume valuable project resources as they are prone to human errors, are highly seasonal, and often require the gathering of unstructured data and of non-consolidated institutional knowledge. Modern RPA software is AI-integrated and features low-code or no-code development environments that allow less technically capable staff, to implement document recognition and sentiment analysis "bots," to efficiently automate document generation and data extraction.

Likewise, the use of computational and simulation models in engineering will allow for iterative exploration and better project results.

In the case of immersive visualisation technologies such as CAVE, AR and VR solutions, recent advancements in electronics, graphics optimised datacentres, GPU technology and ray-tracing have allowed for smaller, lighter, and better integrated XR visualisation tools. These visualisation technologies improve spatial understanding and help design validation in large AEC projects, allowing stakeholders to design, explore and interact with virtual construction models, helping identify potential flaws and other conflicts of concept or design before the project moves to the construction phase. Typical examples of these technologies include Microsoft's *Hololens™* and Meta's *Quest™* headset. AR-capable devices that can overlay virtual construction elements onto the real world, providing accurate visualisation of planned structures in their actual context in the project site. VR-enable devices enable teams to conduct fully simulated walkthroughs, facilitating decision-making online, while eliminating the need for member trips. This reduces the likelihood of costly rework and the need for costly, time-consuming, high-carbon footprint trips (Brozovsky;Labonnote;& Vigren, 2024).[2]

3.4 Enhanced design and optimisation

Traditionally, engineering methods and practices have been constrained by limitations in time and resources, to explore only a small set of scenarios. These evaluations would typically be calculated manually, restricting the possibility of finding other optimal solutions that would balance performance, cost, sustainability, etc. The digitalisation of the engineering process has removed these constraints by abstracting and virtualising concepts, integrating computational methods and tools, and automating calculations and analysis, opening the way for new possibilities and increased performance. (Manzoor, 2021) (Roland Berger, 2016), for example, by integrating BIM with design, construction and operational data, big-data analysis, and advanced computational models of structural and energy us, to simulate multiple iterations and environmental conditions, such as resource availability and cost projections, to deliver better-aligned engineering decisions. (Lavikka;Kallio;Casey;& Airaksinen, 2018) (Manzoor, 2021) (Roland Berger, 2016)

This ability to simulate conditions and outcomes improves individual projects and enhances project portfolio. Engineers can now optimise designs to achieve better outcomes and learn

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[2] On the other hand, these technologies are experimental or have failed market adoption and are being retired as in the case of Hololens. In the case of AI products and services, they are experiencing a "hype" cycle. While potentially extremely useful, still must deliver tangible gains decoupled from high costs and high energy demand. AI and ML applications targeting the AEC the industry are being developed.

about deeper cause-and-effect connections. When applied to the AEC sector data-driven applications done with ML and NN, will enhance optimal solution finding. They do this by projecting known cases to the realm of unknown, interdependent variables. (Chen X. C.-R., 2024) (Brozovsky;Labonnote;& Vigren, 2024) (Manzoor, 2021). These computational capabilities increase the accuracy and efficiency of engineering simulations, improve the modelling processes, and help address uncertainty, leading to more reliable assessments by substituting traditional methods with innovative techniques (Solorzano & Plevris, 2022) (Markou;Bakas;Chatzichristofis;& Papadrakakis, 2023).

The computational first paradigm, radically transforms the engineering decision making process, enabling for the exploration of near-infinite potential solutions, reducing the inherent risks of designing for the unknown, design flaws and human inefficiency. The result is a substantial increase in quality and adaptability, ensuring the diverse demands of modern construction and infrastructure development are met.

4 Digital skills gaps in the AEC industry

The AEC industry's shift towards digitalisation requires a workforce with the necessary digital skills and knowledge. Governments and industry must cultivate this proficiency to ensure a successful digital transformation. The first step involves identifying specific digital skills needed for different professions within the construction sector. For example, architects may need BIM software skills, while site managers might require familiarity with drones for progress monitoring. Likewise, structural engineers may need programming knowledge to explore outcomes of technical decisions effectively before implementation. It is equally important to analyse the existing workforce's digital literacy by evaluating employees across various job categories and seniority levels. This is even more crucial for small and medium-sized enterprises and public offices, which tend to experience significant gaps in digital adoption and skill levels. Monitoring emerging digital trends and consulting with technology experts, will help predict future skill demands to remain ahead of rapid technological changes.

4.1 Understanding the skills gap

The AEC sector groups a variety of professions under the same flag. These professions have diverse needs, but more importantly, they must be able to coordinate with other AEC professionals to provide a cohesive solution. This means that a range of digital skills, requirements and needs exist. Proper assessment to specify the needed technical competencies and specific digital skills needed for each role is crucial (Chen, ym., 2023) (Roland Berger, 2016), and as previously mentioned, an evaluation of the current digital capabilities of the workforce across different job categories and seniority levels, identifying expertise areas where training and upskilling is needed will help in planning interventions were needed. (European Commission, 2019)

Digital technologies evolve more rapidly than others, fuelled by computing performance doubling every eighteen months[3]. Anticipating future skill demands by analysing trends and incorporating those skills into training programs should prepare the workforce for

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[3] David House's generalisation of Moore's Law when factoring transistor count and speed improvements.

upcoming advancements and technological changes (Brozovsky;Labonnote;& Vigren, 2024) (Bosch-Sijtsema;Claeson-Jonsson;Johansson;& Roupe, 2021).

4.2 Recommendations for action

Tailored study programs and curricula must be designed to target the unique digital skills needed for different job categories, offering flexible learning opportunities, including workshops, on-the-job training and certifications to address different learning preferences and life situations. Apprenticeships and internships will ensure practical experience in digital construction for the future workforce. Transforming companies into “learning organisations” by promoting and establishing a culture of lifelong learning and continuous developmentensures the workforce remains adaptable and well-equipped to deal with the evolving digital landscape. Facilitated knowledge sharing should be encouraged by creating platforms for employees to share expertise and best practices and to increase institutional knowledge. Study programs should simulate real-world challenges and focus on practical issues to increase knowledge retention. (American Society of Civil Engineers, 2006) (European Commission, 2019) (Brozovsky;Labonnote;& Vigren, 2024) (Manzoor, 2021)

Collaboration between sector businesses and educational institutions is needed for curricula to reflect current and future digital skills required by the AEC industry. Government and public institutions should promote learning opportunities, explore grants, and fund schemes to support digital skill development in the sector. Partnerships should encourage collaboration between agencies and associations to develop and deliver training programs to fully bridge competency gaps and unlock the full potential of digitalisation. (European Commission, 2019) (Roland Berger, 2016)

Active and mandatory training can lead to higher engagement and knowledge retention by compelling participant involvement. Nevertheless, voluntary programs can be equally effective if they are well-designed and relevant. However, ultimately, the effectiveness of any training initiative depends on its design, relevance, and ability to engage and motivate participants, supplemented with incentives such as professional development and recognition. Offering a range of training options, such as workshops, webinars and online courses can improve accessibility and cater to diverse learning styles and scheduling needs. This is especially crucial for voluntary programs where participants may have limited time and resources. More importantly, creating a culture that values continuous learning, a culture that supports employee development and reinforces and rewards the value of professional growth will significantly increase employee impact in everyday work processes, help embrace novel technologies, and drive innovation throughout the business.

5 The state of engineering education in Finland

Finland's Digital Compass Report (Finnish Government, 2022) identified key digital skills and competencies and states that universities are expected to produce skilled digital professionals with the aim of strengthening global competitiveness and improving research. Higher education intuitions are expected to play a role in developing digital literacy and advanced skills across disciplines. A broad-base education is emphasised as crucial for Finland's digital success. According to the report, Finland faces a shortage of professionals in this area[4].

5.1 Formal tertiary education

The report signals that universities and universities of applied sciences are expected to expand continuous learning opportunities in digital skills to help the workforce adapt to the digital transformation and dictates that digital literacy training should be embedded in all fields of study. For this thesis, limited research was conducted to find what is currently being offered by universities and polytechnics in their curricula, in terms of computational knowledge, and in relation to civil or structural engineering degrees, as exploring all AEC-related areas of study would exceed and deviate from the thesis goal. The programs researched were[5]:

University	Program in	Reference
Aalto University (Aalto)	Engineering degree in Civil Engineering	(Aalto University, 2025)
Tampere University (TUNI)	Master Programme in Civil Engineering	(Tampere Yliopisto, 2025)
Tampere UAS (TAMK)	Degree program in Civil Engineering	(Tampere Ammattikorkeakoulu, 2025)
Lappeenranta-Lahti University of Technology (LUT)	Continuing Education courses	(LUT Yliopisto, 2025)
Häme UAS (HAMK)	Civil and Urban Engineering Education	(Häme Ammattikorkeakoulu, 2025)
LAB UAS	Civil and Urban Engineering	(LAB Ammattikorkeakoulu, 2025)
NOVIA UAS	Building and Civil Engineering	(NOVIA UAS, 2025)
Kaakis-Suomen UAS (XAMK)	Civil Engineering	(XAMK Ammattikorkeakoulu, 2025)
Kaakis-Suomen UAS (XAMK)	Industrial wood construction	(XAMK Ammattikorkeakoulu, 2025)
University of Oulu	Civil and Urban Engineering	(Oulun Yliopisto, 2025)

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[4] Note: As of the writing of this thesis in 2025, the situation is the same. The current level of unemployment (YLE, 2024) in highly skilled employees and a large amount of ICT graduates without a job due to large-scale redundancies paint a vastly different picture.

[5] Program and study names appear translated from Finnish to English, for language consistency.

Aalto University program in construction engineering provides the typical comprehensive foundation curriculum for engineering, including mathematics, physics and technical design and includes courses that explicitly develop computational competencies that go beyond basic IT skills, with courses such as basic and advanced programming (CS-A1111 CS-A1121), machine learning (CS-C3240), databases (CS-A1150), data structures and algorithms (CS-A1141) and IT Applications (CS-C1130). Other mathematics-oriented courses, like numerical analysis and optimisation, are part of the degree. These courses show that the program includes the application of a computational thinking approach and computing skills to solve engineering problems in a structural engineering context. The university also offers a master’s in computational engineering, designed with a computer science approach to engineering.

At Tampere University (TUNI+TAMK), the curriculum designed to impart essential and advanced knowledge in building and civil technology. Basic IT, CAD, BIM, and FEM courses are offered, but nor the bachelor’s nor master’s degrees include dedicated computational science or programming-related courses.

Lappeenranta-Lahti University of Technology (LUT) offers a range of continuous education courses centred on computational technologies that are applicable, directly or indirectly to the built environment. BIM, inventory modelling, data analysis and visualisation are offered; however, no specific degrees with focus in structural or civil engineering are included. Similarly, LAB offers Infra-CAD, BIM, and GIS.

Häme UAS (HAMK) offers a civil and urban engineering degree, but the structure does not offer any other course apart from CAD basics and Geotechnics (GIS).

NOVIA UAS offers a combined building and civil engineering degree that includes CAD and BIM courses. However no computational thinking or computational skills courses are part of the study plans. The construction planning studies in Vaasa offers FEM as part of the studies.

XAMK offers a civil engineering degree, but the degree structure does not offer any other course apart from CAD basics. An industrial wood construction degree exists covering enough engineering to fall under the term of structural engineering. It does offer a set of elective digital and data-science that include Introduction to programming (MO00DS11), Data Analysis (MO00AA05) and Digital Security (MO00AA07)

Oulu University offers bachelor's and master's studies in civil engineering that include solid technical foundations, and like the other universities offer BIM, CAD, GIS, and FEM but offer no course focusing on computational design or computer science.

The outlier among the universities of applied sciences is Metropolia UAS, offering a comprehensive master's centred in VDC. The degree includes programming and algorithmic assisted design, ontology for the built environment, data gathering, data management and data security and AI applications in construction. Then again, it is a master's specialisation course in construction information technology and digitalisation of the built environment, not a degree that leads to a structural or civil engineering degree.

University	**Plan**	**Program (ECTS)**	**Computing course (in English)**
Aalto	2024-2026	Bachelor's program in Engineering Science: Civil Engineering (180 sp)	CS-A1111 Basic programming course 1 (5 sp) CS-A1121 Basic programming 2 (5 sp) CS-A1130 Information technology applications (5 sp) CS-A1150 Databases (5 sp) CS-C3240 Machine Learning (5 sp) CS-A1141 Data structures and algorithms Y (5 sp)
Aalto	2024-2026	Master's Program in Building Technology: Structural and computational mechanics and engineering (120 sp):	CIV-E1060 Engineering computation and simulation (5 sp) CIV-E5020 Structures and Architecture: Parametric Engineering D (3-6 sp)
XAMK	2025-2026	Industrial wood construction (240sp)	MO00DS11 Introduction to programming (5 sp) MO00AA05 Data analysis (5 sp) MO00AA07 Digital security (5 sp)
Metropolia	2025	Computing in Construction, Master of Engineering (60 sp)	TX00FE99 Algorithm-assisted design and optimisation (5 sp) TX00FX22 Artificial intelligence in construction (5 sp) AAC718 Python programming (3 sp)

*Strictly computer-science related courses for civil and structural engineering degrees. FEM, BIM, CAD, GIS, compulsory or optional are not shown. Web programming courses are not included. Metropolia UAS Master appears as an exception.

The percentage of computational courses offered in Aalto’s bachelor of civil engineering is the following:

Course Type	**Total Offered**		**Elective**		**Obligatory**	
	SP	Percentage	SP	Percentage	SP	Percentage
Linguistics, Social Science or Economics	27	12,0 %	0	0,0 %	27	18,6 %
Mathematics or Natural Sciences	85	37,8 %	55	68,8 %	30	20,7 %
Engineering	78	34,7 %	5	6,3 %	73	50,3 %
Computer science	35	15,6 %	20	25,0 %	15	10,3 %
Total	225		80		145	

Percentages relative to the total amount of credits being offered not for the minimum required for graduation

When compared to the computing competencies being taught in US faculties of civil engineering, (Ahmed;Nayeemuddin;Ayadat;& Asiz, 2021) found that none of the universities offered explicit basic computing skills, maybe due to the expectation that US high school graduates possess those skills, but that courses in numerical and computational methods were being taught using high-level languages such as MATLAB, MATCAD, and Mathematica.

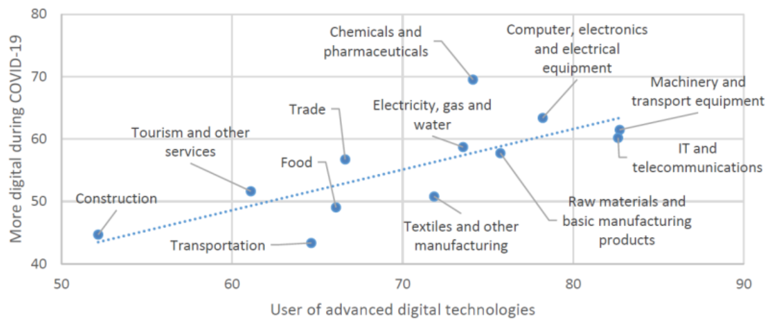
In the few selected US university programs explored for this thesis, it was found that some study programs, such as the Urban Science and Planning offered by the Massachusetts Institute of Technology (Massachusetts Institute of Technology, 2025), offer the possibility of completing computational science related minors, that include algorithms, programming and other similar courses.

All universities offered CAD, BIM, and GIS. Specific training for engineering software is offered, but in general, no specific computational or programming skills are included as part of the curriculum for civil or structural engineers (University of Illinois Urbana-Champaign, 2025) (The City College of New York, 2025). Data science is offered as part of the elective courses at CCNY. Degrees targeting a computational approach to engineering are offered under titles such as “Engineering Physics” at Stanford University, like the master’s in computational engineering offered at Aalto, they are designed to prepare “students to apply modern computational techniques to problems in engineering and applied science” (Stanford University, 2025).

Having reviewed the content of structural engineering curricula across several Finnish and US-based institutions, it could be concluded that a dedicated computational science approach is underrepresented. In Finland in particular, except for Aalto University, which explicitly incorporates programming, algorithms and database design into the curriculum, most programs do not embed any computational content studies directly or as a peripheral part of broader technical courses. In conclusion, while digital tools and methods may be used across the studies, a clear gap in providing a distinct, comprehensive computational thinking approach to engineering, that would fully equip students with advanced algorithmic and simulation capabilities for modern engineering challenges, is missing.

5.2 Continuous learning in the workplace

The European Investment Bank in the survey reports for 2020 and 2023 (European Investment Bank (EIB), 2020) (European Investment Bank (EIB), 2023) evidence the critical state of investment in digitalisation and digital training in the EU. In the EU, the construction industry’s investment in digitalisation remains at the tail end when compared to other sectors and in general, the investment in employee training for the EU27 is not great either, with less than 50% of the construction companies having roughly 50% of users of advanced technologies.

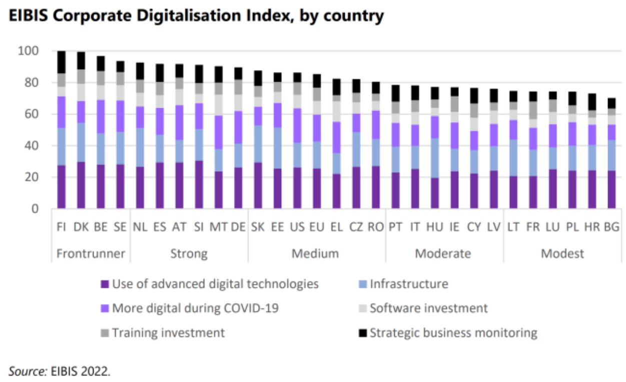


Investment in digitalisation (% of firms)**, by sector**

Source: EIBIS 2022.

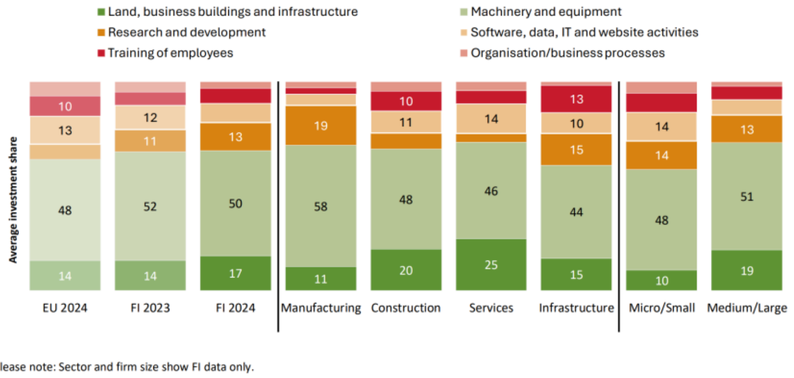
Figure 5-1 Investment in Digitalisation by sector (source: EIIBS 2022)

Finland, based on index, appears as a frontrunner in corporate digitalisation, but in terms of investment in training of employees, research, and development, and in software, data and IT, Finnish firms are on par with the EU average. In terms of specific industries, the Finnish construction sector invests more than its European counterparts in machinery and equipment, but the average investment share in terms of employee training is around 10%, the same value as the EU average. In research and development, it tallies at 11%, 2 points lower than the European average. In other words, in general Finland does fair better, but in terms of the construction industry the numbers are not that promising (European Investment Bank, 2025).



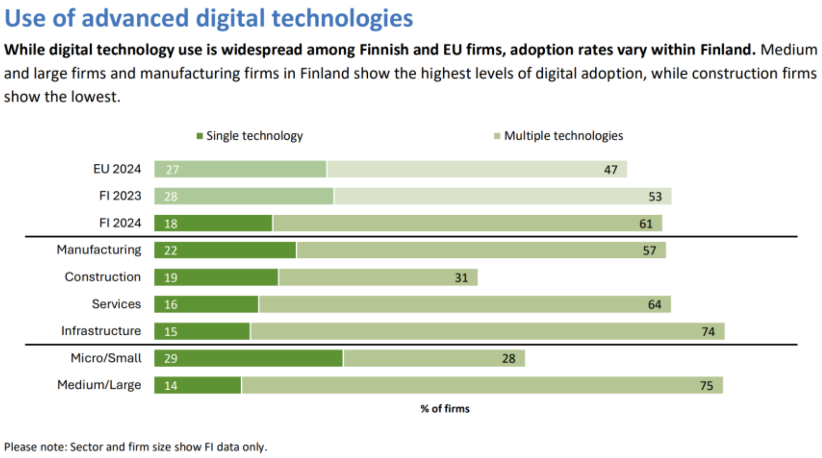
Source: EIBIS 2022.

Figure 5-2 Corporate digitalisation index (source: EIBIS 2022)



Please note: Sector and firm size show FI data only.

Figure 5-3 Average investment share FI vs EU27 (source: EIBIS 2024)



Use of advanced digital technologies

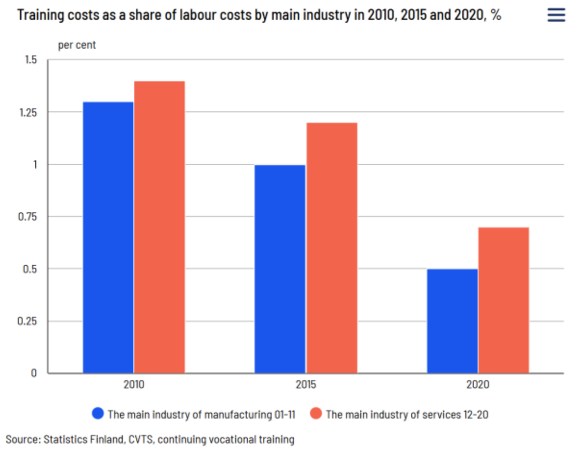
While digital technology use is widespread among Finnish and EU firms, adoption rates vary within Finland. Medium and large firms and manufacturing firms in Finland show the highest levels of digital adoption, while construction firms show the lowest.

Please note: Sector and firm size show FI data only.

Figure 5-4 Use of advanced digital tech FI vs EU27 (source: EIBIS 2024)

Looking closer at the available data, the reported use of advanced digital technology by the construction and infrastructure industry in Finland, is the lowest of all other industries. In terms specific to training, the Finnish National Statistics Institute points to a bleak picture

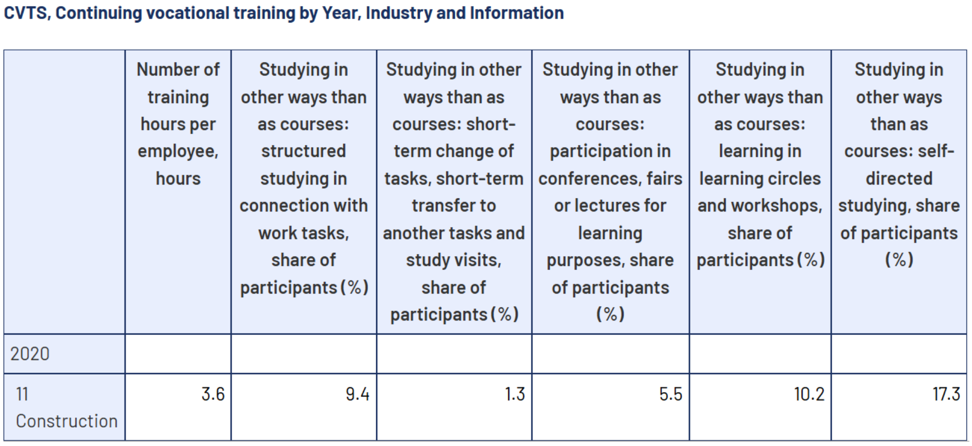
(Stat.fi, 2025)[6]. According to the latest available data, the Finnish construction industry provides, on average 3.6 hours per employee per year in training, with the average investment for the "main industry of manufacturing" (0-11, 11-Construction) being an average of 0.5% as a share of labour costs. Even worse, the spending has decreased by 62.5% (0.75 percentual points) since 2010.



Training costs as a share of labour costs by main industry in 2010, 2015 and 2020, %

Source: Statistics Finland, CVTS, continuing vocational training

Figure 5-5 Training costs as share of labour costs 2010-2020 (source: Tilastokeskus, 2025)



CVTS, Continuing vocational training by Year, Industry and Information

	Number of training hours per employee, hours	Studying in other ways than as courses: structured studying in connection with work tasks, share of participants (%)	Studying in other ways than as courses: short-term change of tasks, short-term transfer to another tasks and study visits, share of participants (%)	Studying in other ways than as courses: participation in conferences, fairs or lectures for learning purposes, share of participants (%)	Studying in other ways than as courses: learning in learning circles and workshops, share of participants (%)	Studying in other ways than as courses: self-directed studying, share of participants (%)
2020						
11 Construction	3.6	9.4	1.3	5.5	10.2	17.3

Figure 5-6 CVTS training hours per employee by industry in 2020 (source: Tilastokeskus, 2025)

The Finnish private sector spent an average of EUR 330 per employee during 2020, a 0.7% as share of the labour costs on average, down from 1.4% in 2010. This suggests that while companies do fund employee training, the investment level has decreased in recent years and it is expected to decrease even further, now that the tax deduction for education for companies is being phased out (Valtioneuvoston viestintäosasto, 2024) (fok.fi, 2024).

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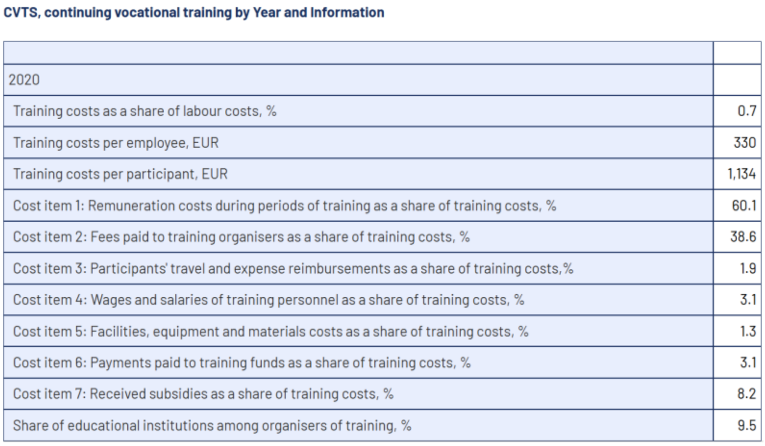
[6] Data refers to continuing vocational training described as "the development of personnel competence" in enterprises and enterprises' training practices.



CVTS, continuing vocational training by Year and Information

2020	
Training costs as a share of labour costs, %	0.7
Training costs per employee, EUR	330
Training costs per participant, EUR	1,134
Cost item 1: Remuneration costs during periods of training as a share of training costs, %	60.1
Cost item 2: Fees paid to training organisers as a share of training costs, %	38.6
Cost item 3: Participants' travel and expense reimbursements as a share of training costs,%	1.9
Cost item 4: Wages and salaries of training personnel as a share of training costs, %	3.1
Cost item 5: Facilities, equipment and materials costs as a share of training costs, %	1.3
Cost item 6: Payments paid to training funds as a share of training costs, %	3.1
Cost item 7: Received subsidies as a share of training costs, %	8.2
Share of educational institutions among organisers of training, %	9.5

Figure 5-7 Continuing vocational training per year and information (source: Tilastokeskus, 2025)

For context, the European average private firm only allocates EUR 232 per employee (Centre pour la recherche économique et ses applications (CEPREMAP), 2022), with many firms allocating well under 1% of labour costs to training. In Finland, despite the low spending, a significant part, 61% of companies, do offer some sort of training, with about 29% of employees participating in formal course-based training (Tilastokeskus, 2020), but when averaged across all employees, it only equates to 5.2 hours of yearly training. In other words, the typical employee in Finland’s private sector received around one day or less of employer-funded training during 2020[7].

Nor the construction industry, nor the private sector might fully represent the space of labour covered by civil and structural engineers, and statistically speaking, Finland’s “Architectural and Engineering activities” (TOL 2008 M71) fall under what is defined as “knowledge-intensive services”. Statistically, these companies invest more in employee training. However, even if the M71 sector invested five times the national average, it would still amount to less than 1 ECTS per year.

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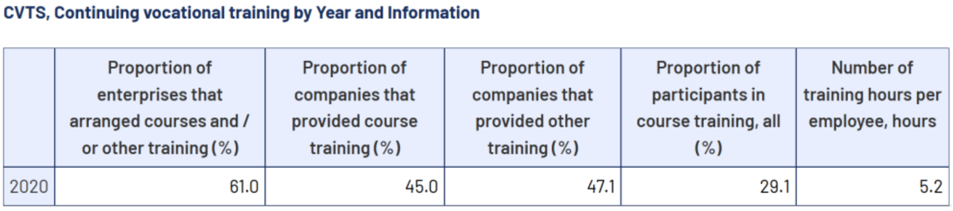
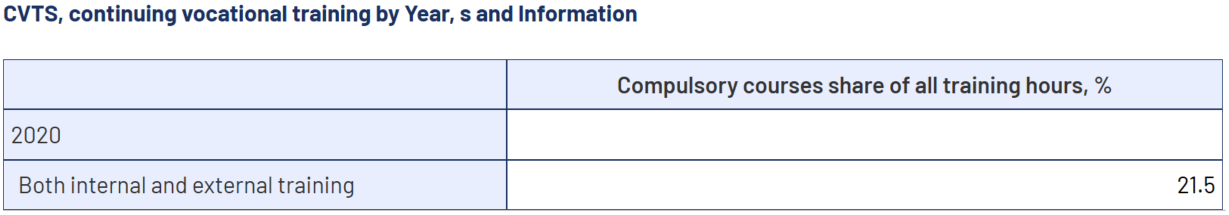
[7] However, those who took part in training may have had longer training duration, about 18 hours of training since 29% participation yields 5.2 hours per employee.



CVTS, Continuing vocational training by Year and Information

	Proportion of enterprises that arranged courses and / or other training (%)	Proportion of companies that provided course training (%)	Proportion of companies that provided other training (%)	Proportion of participants in course training, all (%)	Number of training hours per employee, hours
2020	61.0	45.0	47.1	29.1	5.2

Figure 5-8 Number of training hours per employee (source: Tilastokeskus, 2025)



CVTS, continuing vocational training by Year, s and Information

	Compulsory courses share of all training hours, %
2020	
Both internal and external training	21.5

Figure 5-9 Compulsory courses share of all training hours (source: Tilastokeskus, 2025)

As detailed data about the M71 sector is scarce, it is useful too, to look at the broader European pattern. When compared to other EU member firms' training, investment by Finnish firms averages on the lower side (Eurostat, 2022). With moderate training costs of EUR 1120 PPS per employee and a training offering lower than that of the EU average, 61% versus 67%, Finnish firms place themselves far from private firms in countries such as Sweden, where between 80 to 90% of the companies provide continuous training and spend EUR 1485 PPS per-employee. It should be noted that according to Eurostat, when "compared to 2010, the hourly cost of training increased in most countries and only decreased in Croatia, Finland, Germany, Portugal, Greece and Hungary" (Eurostat, 2022). This suggests that the overall training provision for the Finnish enterprise is a bit below that of the European median, in other words, Finnish firms are "engaged in training, but not at the top of the league" with an across-the-board investment in continuous learning remaining relatively low in proportion to overall labour costs.

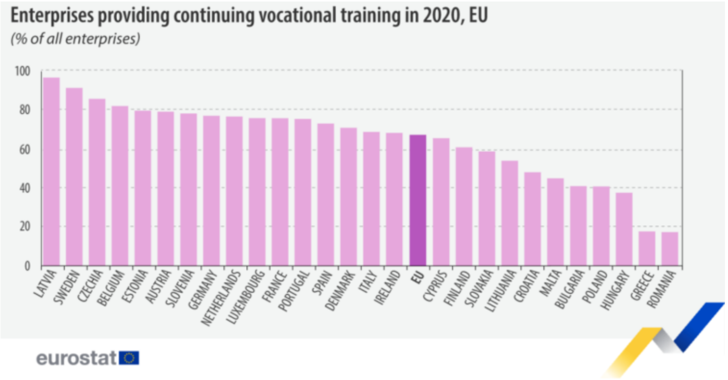
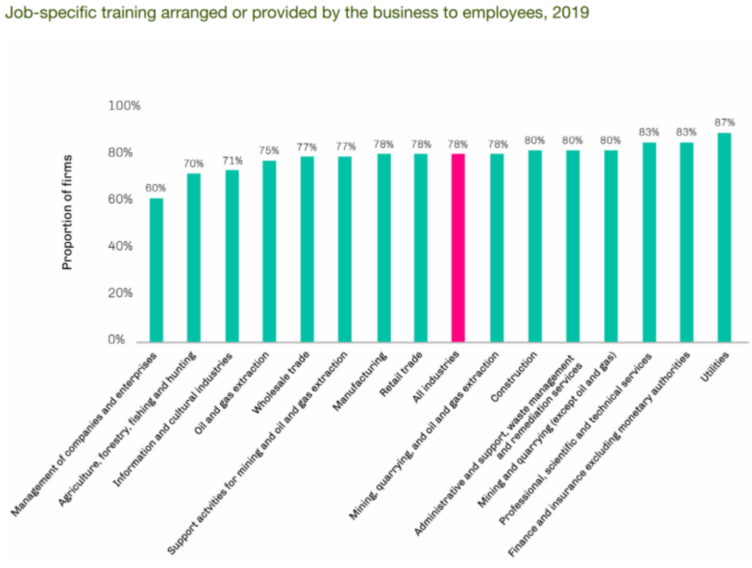


Figure 5-10 Enterprises providing vocational training in 2020 in the EU (source: Eurostat)

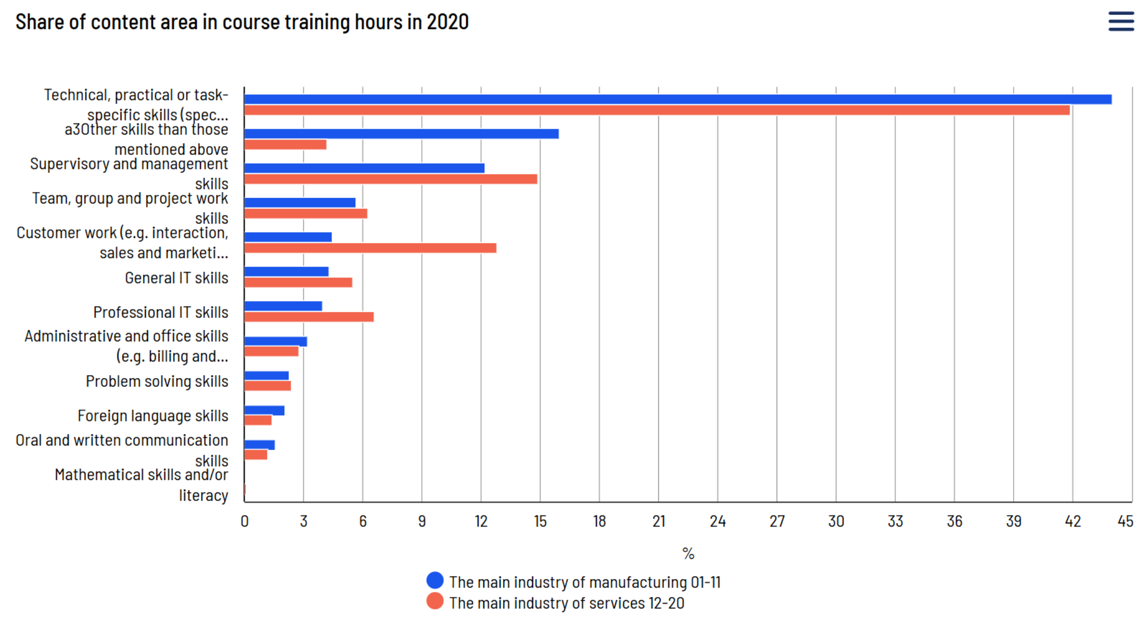
For comparison, in the United States the "Association for Talent Development" reports a slightly higher absolute annual spending per employee of approximately $US 1300 (EUR 1199) invested on learning (Association for Talent Development, 2022) and in Canada the (Business Council of Canada, 2022) reports 45% of private firms invest over $CAN 1000 (approx. EUR 650) per employee per year. In Canada, 83% of professional, scientific and technical industries, are more likely to invest in training according to the 2020 Survey of Innovation and Business Strategy (Statistics Canada, 2019).



Source: Survey of Innovation and Business Strategy
Sample: 14,985 businesses for 2019 release

Figure 5-11 Job specific training arranged by the business to employees (source: SIBS 2019)

In terms of content, Finnish private enterprise invests the bulk of training hours, around 40%, equipping employees with practical and task-specific skills. Less than 7% of the hours are being dedicated to either professional or general IT skills, and less than 3% on problem-solving skills and a negligible amount in mathematical or literacy skills[8]. In other words, extrapolating these results, there is investment in task completion and supervisory skills, but not on those needed for a computational thinking approach to engineering. This data suggests that meanwhile companies may recognise the need for training, there is a significant potential to expand employer supported upskilling of employees. Unfortunately, the trend indicates the opposite.



Source: Statistics Finland, cvts, continuing vocational training

Figure 5-12 Share of content area in training hours in 2020 (source: Tilastokeskus, 2025)

The lacklustre approach of private industry regarding upskilling might originate in the preference for “hiring skilled labour already available in the market, rather than bearing the costs of in-house training” as described by (Brunello;Rückert;Weiss;& Wruuck, 2023). Yet, according to Forbes, companies with comprehensive employee training programs “enjoy 218% higher income per employee and 24% higher profit margins” (Forbes, 2019).

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[8] In general, mathematical skills in Finland have been decreasing and Government, as well as technological and engineering associations, have ear-marked them as problematic.

Likewise, data gathered from 2009 to 2016, showed that employees who received “employer-sponsored classroom training”, were 11% more productive (Munro & Lamb, 2023), leading to higher employee wages, when more productive and profitable firms share their gains with the employees. In terms of increased productivity, the EIB (European Investment Bank (EIB), 2023) found that spending EUR 1000 on training per employee equates to a rise in productivity between 2.6% to 3.2%. In terms of hours, one hour of training would equate to 0.16% to 2% productivity increase, a value that falls in line with findings by (Almeida & Carneiro, 2009)

On the other hand, and in terms of digital adoption, the European Investment Bank found that firms tend to reduce training investment per employee following the adoption of advanced digital technologies (ADTs). These technologies and traditional training methods are seen to function as substitutes. In other words, ADT replaced tasks previously performed by employees, leading to a decline in the perceived need for upskilling. The reduction of investment in training was found to be between 1.3% to 1.7% per employee per ADT introduced, and every additional point in digital intensity resulted in a reduction of investment between 0.4% to 0.8% per employee (European Investment Bank (EIB), 2023). That is, use of advanced digital technology decreases the productivity of training and discourages further investment in training. When coupled with the tendency to hire already skilled labour, it further contributed to the decline of per-employee training expenditure.

The increase in ADT spending was found to lower the skill requirements for certain tasks, thus reducing the incentive to invest in training. Despite this reduction per employee, the study found that overall firm employment tended to increase. In the case of public training subsidies, the studies showed a positive avenue for mitigating the decline in employer-provided training in the face of increasing ADT adoption. The study also found that countries with limited investment in “active labour market policies,” and limited employer-sponsored training, faced higher risks of widening inequality due to increased digitalisation. It also found that higher public investment in training, helped counteract the tendency of firms adopting ADTs, ensuring adequate skill development in increasingly digital economies.

In conclusion, as firms adopt ADTs, they often reduce investment in employee training, assuming that automation decreases the need for upskilling. However, to fully extract the productivity and efficiency gains ADTs offer, firms still need employees to understand, manage and optimise these technologies. ADT adoption does not eliminate the need for human skills, judgement, creativity, problem-solving and other interpersonal skills. While ADTs enhance efficiency and decision-making, as for example they can process large amounts of data, they lack the ability to make context-aware, ethical, and legally accountable decisions. Oversight requires a "human in the loop" professionally trained to understand how these technologies function, their limitations, potential biases, and the implications of their outputs. This is particularly crucial in the case of AI and ML systems.

Ensuring that "human employees[9]" have the technical knowledge, critical thinking skills and ethical training to interpret, refine and override automated decisions and processes, is essential to maintaining fairness, transparency and accountability. Employees who can effectively integrate ADT into their workflows will innovate better, reduce inefficiency, and ensure a smooth digital transition. Rather than seeing ADTs as replacements for training, firms should invest even more in upskilling to have it function as a force multiplier, ensuring business growth and long-term success in the digital era. To ensure economic stability, equality and competitiveness, governments must actively support and incentivise workforce training in the face of increased digitalisation and automation, to reduce job displacement risks and inequality increase, and to ensure that employees and businesses can fully leverage the benefit of the digital transformation.

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[9] As opposed to the "AI coworker."

6 The future of engineering education

The rapid digital transformation of the AEC sector raises the issue of how engineering education can adapt to equip current students with essential skills while keeping core engineering knowledge. Foundational engineering principles are critical for understanding behaviour and response in physical systems. These principles build on well-known but essential mathematical and physical principles, that provide the basis to solve complex engineering problems involving material properties, structural integrity, and motion. A solid understanding of continuum mechanics for modelling various physical phenomena such as vibration, plasticity, heat transfer, represented through partial differential equations and solved using numerical methods is also needed (López;Estrella;Vázquez;Velázquez;& Molina, 2024). These essential courses are taught from a classical perspective, and do not integrate digital skills crucial for preparing graduates to help in the evolving digital integration.

6.1 Curricula, pedagogy, and skill development

Integrating digital skills early within existing courses offers a practical solution to time and curriculum constraints. Instead of being taught through dedicated stand-alone courses, digital skills can be embedded with traditional engineering subjects. Even minimally integrating them, for example, incorporating a single problem per assignment involving coding or data analysis, can significantly reinforce skill gain. Laboratory activities to bridge the gap between physical and digital models, can help students explore and understand how design parameters influence system behaviour through modelling and simulation (Magana & Coutinho, 2016). A multidisciplinary approach to education, blending engineering and computing, is critical for developing “well-rounded” engineers proficient in core competencies and digital skills such as programming, machine learning, and digital manufacturing. Concepts that will equip future engineers with a robust set of digital skills while maintaining a firm foundation enabling them navigate the complexities of digitalisation effectively and to meaningfully contribute to the advancement of the engineering profession while fostering a holistic understanding of real-world complex systems (Lena Gumaelius, Inga-Britt Skogh, Ásrún Matthíasdóttir & Panagiotis Pantzos, 2024).

As digitalisation and abstraction of concepts allow for rapid evolution of the technological framework, engineering programs must foster an adaptable, continuous learning mindset in their students, ensuring they have the highest chance to thrive in their professions after graduation. Networked learning research, problem-based learning and other hybrid learning pedagogical approaches could help, too (Laursem, 2025). Soft skills such as teamwork, team dynamics, leadership, and ethics are vital; promoting a mentality shift to focus from learning specific technologies to fostering the capability to learn new ones is equally so, and this requires flexible curriculums that emphasise lifelong learning strategies (BGZ Berlin International Cooperation Agency, 2023).

Cultivating the development of a “computational mindset” will enable students to approach engineering challenges with a problem-solving orientation, a way of thinking that embraces a computational approach to problem solving, going beyond specific software or programming languages (McCord;Gheisari;& Mutis, Computing in AEC Education: Hindsight, Insight, and Foresight, 2024). An environment that fosters and encourages exploration, innovation, and tolerance for failure (AntonioL.Leal-Rodríguez;CarlosSanchís-Pedregosa;AntonioM.Moreno-Morenob;& AntonioG.Leal-Millan, 2023)

From an academic performance perspective, computational knowledge significantly enhances the engineering student’s problem-solving capabilities. A meta-analysis conducted by (Hidayat, ym., 2024) revealed that computational thinking skills positively influence academic achievement with an overall effect size of 54%. Also, computational thinking skills lead to improved grades in courses that incorporated them as shown by (Dehbozorgi & Roopaei, 2024). By promoting problem decomposition, abstraction, and pattern recognition, all of them crucial for addressing complex engineering problems, students become better equipped to solve academic and professional challenges.

6.2 Technology Integration

The digitalisation shift in the AEC industry emphasises the need and value for CAD skills such as 2D and 3D drafting and documentation, the use of simulation, VDC tools such as FEM and CFD, numerical methods, BIM etc. (McCord;Gheisari;& Mutis, Computing in AEC Education: Hindsight, Insight, and Foresight, 2024). Yet moving beyond basic computing proficiency to include programming, data analysis, and computational design is increasingly important as projects get more complex and as data grows (McCord;Gheisari;& Mutis, Computing in AEC Education: Hindsight, Insight, and Foresight, 2024). Thus, digital literacy and programming skills have been identified as fundamental for the workforce, in any position, to face the digitalisation process of engineering in construction (Souza & Debs, 2023)

Low-level languages such as C/C++ will remain valuable in the right hands, for computing tasks that need speed and complexity, but for most AEC engineers, Python is the best alternative. Python has become the programming "Lingua-Franca of science" in the last two decades and allows for rapid gain of computing capabilities. Python is a highly versatile, extensive and relatively easy-to-learn programming language, but formal instruction is lagging according to education professionals (McCord;Gheisari;& Mutis, Computing in AEC Education: Hindsight, Insight, and Foresight, 2024).

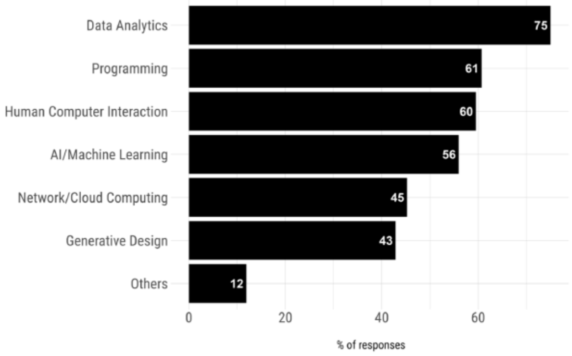

Figure 6-1 Percentage of respondents who indicated each advanced computing literacy would be relevant to their students in their future success. (McCord et al. 2024)

Visual programming languages and environments like Dynamo, Grasshopper and FME are evolving and gaining traction as they simplify programming tasks, balancing user-friendly interfaces with hard computational skills while promoting solution exploration through "multidimensional parametric modelling and optimisation." In these environments, the user explicitly maps data flows from input to desired outputs by focusing on data rather than on specific programming-language knowledge and programming skills. Nevertheless, the computational mindset needed to achieve a solution is the same. The user still must be able to plan and implement programming patterns and to subdivide and debug algorithms (McCord;Gheisari;& Mutis, Computing in AEC Education: Hindsight, Insight, and Foresight, 2024). There would also be a need to include and develop a strong foundation of other computer science principles to build upon, but here again, engineering discipline curricula lags in providing the necessary skills (Abell;Moreno-Casas;& Recabarren, 2024).

6.3 Meeting future trends

Engineering education must evolve to meet future industry requirements. These changes will involve modernising curricula, adopting new pedagogical approaches and, to some extent, putting more emphasis on interdisciplinary knowledge.

Curricula for classical engineering degrees will have to keep up with the rapid pace of computing and technological advances. The requirement for a digitalised industry demands that graduates can solve technological problems in their field and work across disciplines (López;Estrella;Vázquez;Velázquez;& Molina, 2024). Thus, “Engineering Education 4.0” needs to assess the application of “disruptive technologies for learning” based on competencies, processes, technologies, and didactic methods.

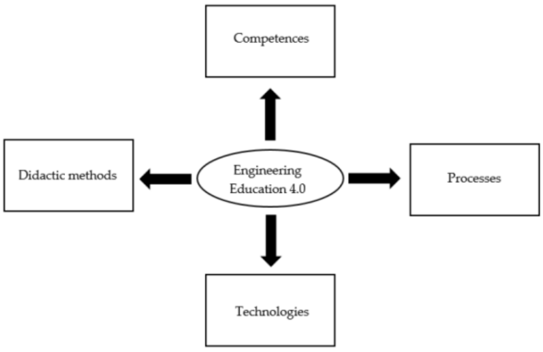

Figure 6-2 Engineering education 4.0 basis (source: López et al. 2024)

As such, institutions must collaborate with industry to update content that moves beyond their foundational knowledge. The future industry needs more “T-shaped” engineers. Interdisciplinary engineers whose adaptability and focus on computational capabilities, allows them to address the shifting dynamics between technology and its application in the AEC disciplines. Equipping students with a computational background allows them to abstract knowledge and better respond to changes, as digital transformation is not only happening faster than universities might be able to react to but is also highly unpredictable.

Universities can (potentially) benefit from integrating technological advancements such as LLMs, Digi-rooms and asynchronous learning methods. These tools could serve as co-teachers, offering assisted engagement to achieve the goal of helping students develop skills such as critical thinking, creativity, and a lifelong learning mindset. In other words, courses should focus less on teaching concrete technologies and more on techniques on how to acquire know-how (Lena Gumaelius, 2023). But it is not all necessarily positive.

In the case of AI in education, the monopolisation of AI can significantly affect who benefits from “AI-enhanced” learning. Many “AI educational tools” such as intelligent tutoring systems and assistants come with subscription and licensing fees raising concerns that their cost could put low-income and under-resourced schools, at a disadvantage (EDUCAUSE Review, 2024). Monopolisation of AI may lead to overdependence on proprietary systems leaving educational institutions trapped by educational technology industries and leading to privatisation and corporate takeover of higher education.

In terms of cognitive skills, a recent study published by Microsoft and Carnegie Mellon University (The Impact of Generative AI on Critical Thinking: Self-Reported Reductions in Cognitive Effort and Confidence Effects From a Survey of Knowledge Workers, 2025) found that the more users lean on so-called “AI tools” to complete their tasks, less critical thinking they do. The study showed that the higher the confidence of the user on the “AI tool,” the lower the critical thinking effort the user did. This led to potential over reliance, diminished awareness, motivation, self-confidence, and ability. In other words, that even when ML tools have the potential of increased efficiency and better results, the lack of knowledge on the tools limitations and functionality and the user overreliance, come at a cost in “muscle memory” and “deterioration of cognitive faculties.” When critical thinking, a crucial part of tertiary education, is undermined, public interest and values may be at risk in the long term.

To illustrate with a simpler example, the availability of calculators does not justify ending mathematics courses for engineering students. Instead, education should focus on understanding technical limitations and proper usage of such tools, while also fostering critical thinking skills. This ensures that students understand how structured mathematical calculations are executed within these devices.

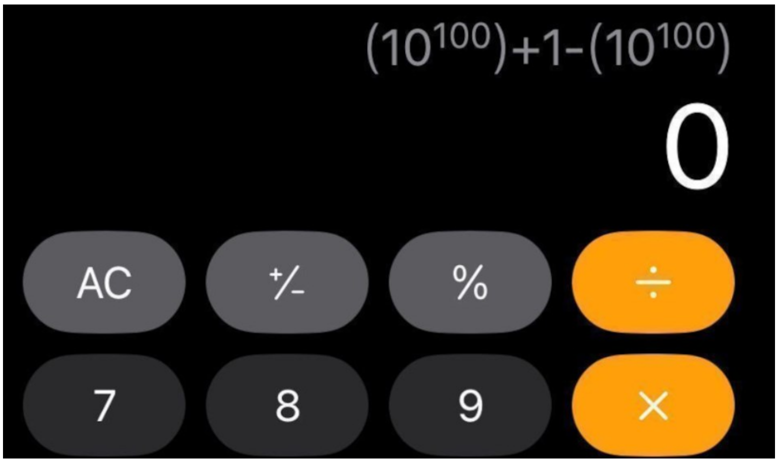

Figure 6-3 Calculators and computers are good at math

6.4 Barriers to adoption

Other barriers in engineering education hinder the adaptation of curricula to meet future digital needs. Institutional and legal constraints, insufficient resources, lack of accreditation and lack of digital skills in faculty limit the evolution of curricular programs, highlighting the need for updated frameworks and consistent support so that graduates meet current and future needs.

Institutional and systemic barriers, short of being a nuisance for teachers, cut short their ability to help students. Inadequate resources and funding, including insufficient resources to make curricular changes, acquire infrastructure and provide adequate teaching assistance and student support, are significant obstacles. Time constraints impede broader improvements, in the case of universities, for example, when primary focus is on research and not on pedagogical advancements. Inadequate support from administrators and regulators also hinders the development of programs and restricts the capability of teachers to implement them (European Commission: Executive Agency for Small and Medium-sized Enterprises (EASME), 2020).

Other prominent barriers to incorporating new knowledge mentioned in the literature are the “overloaded and restrictive curriculum,” and the absence of accreditation criteria for computing competencies that can reduce the incentive for universities to prioritise these skills (McCord, ym., 2024) (Magana & Coutinho, 2016) (Kelley T. , 2008).

Personal barriers and resistance from educators and students, who may not see or do not want to change, are a significant obstacle too. Pre-established beliefs, lack of motivation, preference for traditional theory-driven teaching approaches, and lack of competency in relevant digital skills, can result in negative learning experiences and resistance to digital transformation. Deficiencies in programming and mathematical skills are challenges to introduce modelling and simulation and may reduce the impetus for curricular changes.

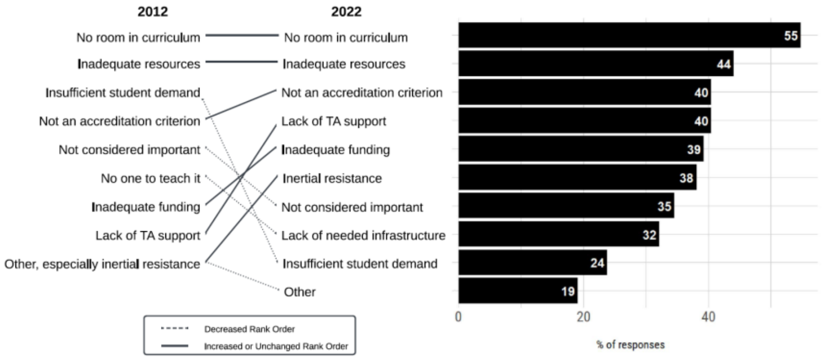

Figure 6-4 Barriers to adoption of CT skills in engineering degrees (McCord, ym., 2024)

Establishing agreements from all stakeholders in the educational framework is needed to enact changes that address its core mission and identity in a fast-paced, changing environment where the relationship and integration between humans and digital technology evolves and advances at high speed. Educators must equip students to engage with emerging technologies and lead technological innovation, and to integrate those computational skills in the curricula successfully, instructors need to have those skills and knowledge. They need support, retraining, educational reforms, proper infrastructure, and funding to ease those educational shifts (McCord;Gheisari;& Mutis, Computing in AEC Education: Hindsight, Insight, and Foresight, 2024).

Other identified barrier is the lack of consensus on definitions in the context of computational thinking (Zhang;Torre;& Specht, 2022) that hinders the development and integration of computational skills in engineering curricula. Traditional approaches and “silo-thinking” that dominates teaching approaches are a problem too (European Commission: Executive Agency for Small and Medium-sized Enterprises (EASME), 2020). Other examples of barriers are, the belief that computing is only using commercial software (Talaat;Kohail;& Ahmed, 2022) leading to neglect of programming as a valuable tool, difficulty in assessing and evaluating computational thinking, lack of guidelines and difficulty in measuring the impact of computational thinking in higher education (Zhang;Aivaloglou;& Specht, 2024).

Funding is also a barrier. In Finland, at the administrative level, tertiary education represented 1.4% of the expenditure as a percentage of GDP in 2021 (European Commission, 2024). As of 2025, the budget proposal reduces the investment in vocational education and training by EUR 120 million (Finlands Ministry of Education and Culture, 2024) and includes cuts of up to EUR 250 million to the administrative branch of the Ministry of Education and Culture by 2028 (Finnish Union of University Professors). With limited funding, engaging in the needed curricular changes will be difficult.

6.5 Visions of the future

Educators must reimagine engineering curricula and teaching methodologies to adapt the learning process to the changing landscape, given the accelerating pace of technological innovation and the shorter time-frames available to reflect on current educational programs. Hybrid skillsets and lifelong learning skills might prove better at helping engineers adapt to unpredictable technological advancements. In that sense, the abstraction of processes and a forward-thinking approach could help engineering graduates become proficient in the “core” traditional engineering principles and any future change. Likewise, teachers must engage in continuous professional development. They might need to adopt new pedagogical strategies that move from a theory-heavy learning program to a flexible, interdisciplinary, project-based learning model that includes data and computational thinking. The future of engineering education must prepare the next generation of engineers for the digital world. This transition will redefine engineering practice and reshape the educational landscape as the rapid evolution of technology means that acquired competencies will become obsolete within the graduate’s working lifespan.

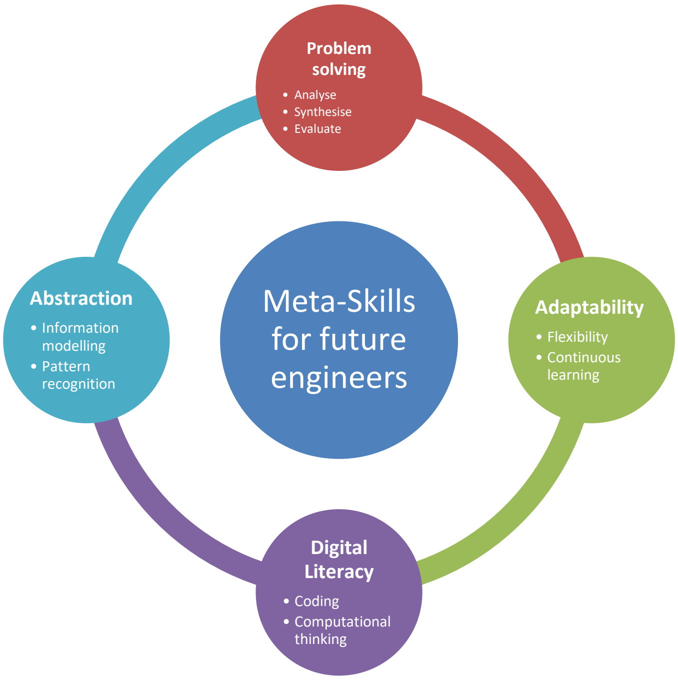

Figure 6-5 Meta-skills for the future

The future of engineering education is a flexible, digital-first and industry-integrated revolving door where universities transition from purely academic gate-keeping institutions to hubs of innovation, digital experimentation, and life-long learning. Faculty members become mentors, facilitators and interdisciplinary researchers who guide students. Curricula will blur boundaries between engineering disciplines, integrating computer science, business, environmental studies and others to produce technically capable but flexible professionals, allowing students to upskill and reskill as needed with the coming unpredictable changes[10]. Ultimately, the future of engineering education is adaptive, immersive and abstracted, ensuring engineers remain versatile problem solvers in an ever-changing, highly complex, technology-driven world.

The increased need to integrate computing and information technologies shapes the future of civil and structural engineering. Not only are they taking a progressively crucial role in daily operations in the AEC field, but there is no effective method to manage the vast amounts of complex data needed for current and future projects. The industry needs educators to adjust and reimagine curricula and teaching methodologies so that future professionals can use these technologies more effectively, as they provide a significant

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[10] Just like software engineers load and unload needed libraries for the application’s specific purpose, engineering professionals must learn and unlearn new skills.

competitive advantage. Future engineers must be ready to work more intelligently, efficiently, and effectively than they did before. The education they receive must provide the skills needed to achieve this. Also, the future of engineering practice is expected to rely less on manual repetitive tasks. The education students receive must teach them how to rapidly adapt to technological, professional, and social changes. Computation and "Big Data" should be a core competence in the 21st century. While civil and structural engineering may have historically underutilised programming and computation, there is a growing need for graduates to understand and apply computation skills for data analysis, automation of design and calculations and to interpret code and digital tools done by others and by AI.

Embedded programming courses taught by civil and structural engineering professors, focusing on real-world applications, will be vital for students to cultivate the analytical thinking and problem-solving abilities essential for upcoming professional challenges. Thus, educators must recognise the need to augment current teaching practices, incorporating specific technical and computational thinking and computing skills. The emphasis is on shifting civil and structural engineers, or any other engineering professional for that matter, from simple software users to professionals who drive technological change by utilising computing. It is important to understand that the faster technology outpaces what is covered by the curricula, the more abstract their capabilities must be[11]. From being tool users to becoming tool makers once again.

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[11] While technological and computing skills are crucial, professional leadership, decision-making, problem-solving, and other soft skills ought to be part of study plans too.

7 Integrated framework for the digital industry

As digital transformation accelerates, a comprehensive approach to legal, socio-political, and strategic challenges must be addressed. A cohesive European digital strategy can collectively shape the sector's future and establish the foundations for innovation, sustainable growth and independence.

7.1 Legal considerations of a digital industry

From an engineering perspective, legal aspects must be considered when thinking about a digitalised industry. Just like professional engineers are required by law to know about certain topics relevant to their profession, in a data-centric industry, structural and civil engineers will be legally responsible for the content of their virtualised work.

The digitalisation of the construction industry, with data as the central element, "involves generating, processing, combining, analysing, sharing, and using data throughout the construction project chain. This data includes digital information, drawings, models or other that parties exchange" (Bruggeman E. M., 2022). Likewise, the legal standards are evolving to reflect technological advancements, including interpreting the constructor's responsibility to exercise due care and provide warning, alongside the "doctrine of explanation" concerning the sale of digitalised information and content. In some instances, laws are being revised to accommodate the standardisation of "data requirements and the legal frameworks surrounding those requirements" (Bruggeman E. M., 2022) (Silvia & Yanka, 2022).

Equally, the digitalisation process influences contractual arrangements and obligations, potentially requiring a shift in the qualification of contracts. There is too growing importance attached to the information-sharing responsibility in the new legislation, arising from the mixed nature of physical works, digital services, and contracts. There are too data rights and obligations, statutory or contractual, in "data and data collections that may be subject to intellectual property rights" (Bruggeman E. M., 2022) and trade secrets and obligations towards data that might be subject to privacy rights including, but not limited to, the duty to deliver, transfer, copy, process, collect and share data.

Regarding collection, digitisation and abstraction of information, these processes lead to improved and simplified information exchange and communication, which has resulted in calls to focus contracts on relational rather than transactional approaches to contracts and to initiatives such as the European Digital Single Market Strategy and the Digitising European Industry initiative, along with other national programs to stimulate innovation in the sector. Also, legal frameworks on data requirements need standardisation so that data agreements remain consistent and compliant. Engineers must understand the legal doctrine surrounding those requirements and the contractual obligations related to that data.

Figure 7-1 Legal considerations of digitalised data

As AI and ML algorithms become more prevalent, engineers must be aware of potential biases in data or algorithms that could lead to discriminatory and one-sided outcomes that may perpetuate inequalities. Engineers using or developing algorithmic solutions should strive to reduce impact, ensuring all stakeholders are treated just and fairly, and considering the broader social and environmental impacts of their decisions (Bruggeman E. M., 2022).

In this sense, the concept of an “Industry 4.0,” emphasises the requirement for engineers to manage data throughout the project life-cycle, covering the whole value chain in the construction process, becoming an integral part of the economic process and thus requiring professionals to manage and implement data strategies supporting data quality. In other words, this requires professionals with sufficient digital skills and qualifications to effectively promote, ensure and understand requirements for digital data from a legal point of view. In terms of the data economy, the construction sector is still far behind other markets; this delay, while costly for the industry, could also benefit if stakeholders learn from mistakes happening in other industries. (Amiot;Palencia;Baena;& Pommerol, 2020)

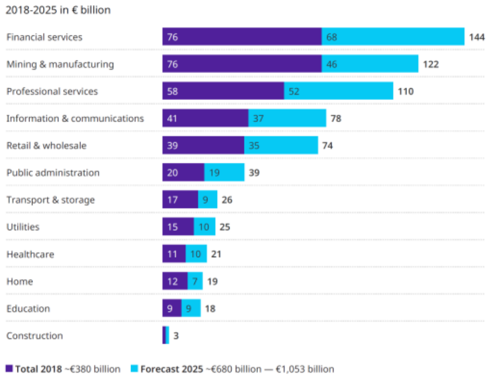


Figure 7-2 Total impact of the data economy per industry in the EU (source: Amiot, Palencia, Baena & Pommerol, 2020)

7.2 Socio-political considerations of a digital industry

The intertwined dependency of digital transformation and digital capabilities in the construction industry’s digital transformation underscores the critical need to increase computational science related education for AEC-related engineering disciplines. By expanding the curriculum or integrating a comprehensive set of computational thinking courses in the current programs, Finland and the EU can simultaneously address the socioeconomical issues derived from the digitalisation of the industry, ensuring greater competitiveness, digital sovereignty, and resilience, while meeting educational, political and strategic goals.

In digital terms, the whole AEC industry is captive of a “Format as a Service” business model, where proprietary file formats require an ever-binding, near mandatory, pay-to-play toll. The EU lacks technical leadership and ownership, with those sectors dominated by non-EU actors. As detailed in the recent analysis by Mario Draghi for the European Union (Draghi, 2024), the consequences of digital dependency include reduced economic competitiveness, erosion of digital and real sovereignty, constrained innovations and vulnerabilities in data security and strategic autonomy. These risks are not just theoretical;

experts from industry, government and academia have described the situation in Europe as a sort of "digital colony," a consumer of technology rather than a producer.

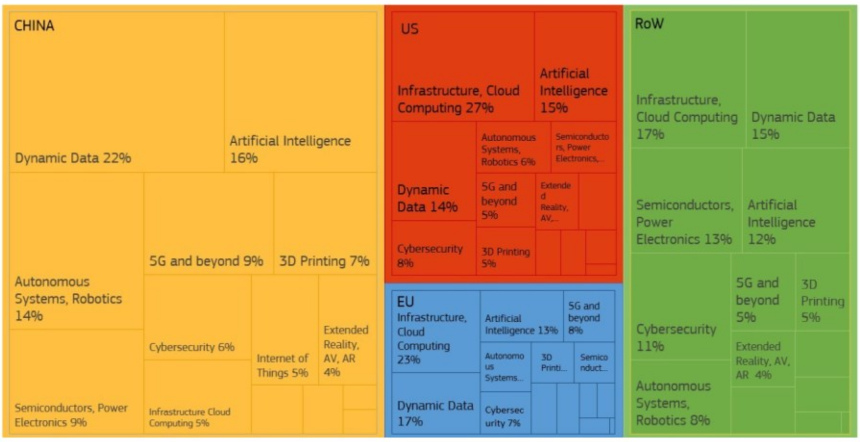


Figure 7-3 EU relies on foreign countries for over 80% of digital products, digital services, infrastructure, and intellectual property (source: Calza et al. 2023)

These economic, social, and political considerations underline the importance of digital capabilities across different sectors, including the construction and educational industries. In this setting, increased exposure of AEC-related engineering graduates to computational science courses is a strategic social requirement and a social investment in Europe's future. It is so that educating future engineers in computational sciences as a way of abstracting problem-solving, will contribute to indigenous digital solutions and capabilities, reducing dependency on foreign actors and platforms. A well-informed technical workforce can navigate, steer and shape evolving frameworks and become crucial for designing technologies that align with EU standards, values and interests, as digital dependency translates into political vulnerability. It is not about technology for technology's sake but a means of safeguarding the "European vision." Likewise, by closing the digital skills gap, generalised computational science education may lead to higher quality jobs, reduced market polarisation and help retain top talent.

In these terms, the real impact of AI and ML is still unclear, but there are clear potential benefits and negative societal consequences. Overall, the monopolisation of AI algorithms in the hands of a handful of players threatens to intensify economic disparities, concentration of wealth and power, depriving smaller enterprises and individuals of the potential benefits of AI and ML. The construction and education industries' use of AI at a

European level is low. However, in the cases of information, professional, scientific, and technical activities, the core aim of this thesis, the use is rapidly increasing. As mentioned before, the use of AI has ethical concerns too, when a small group of corporate entities set ethical standards, as society faces risks due to lack of oversight and accountability.

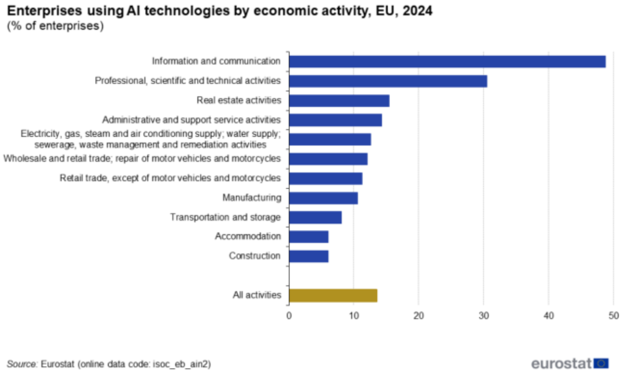
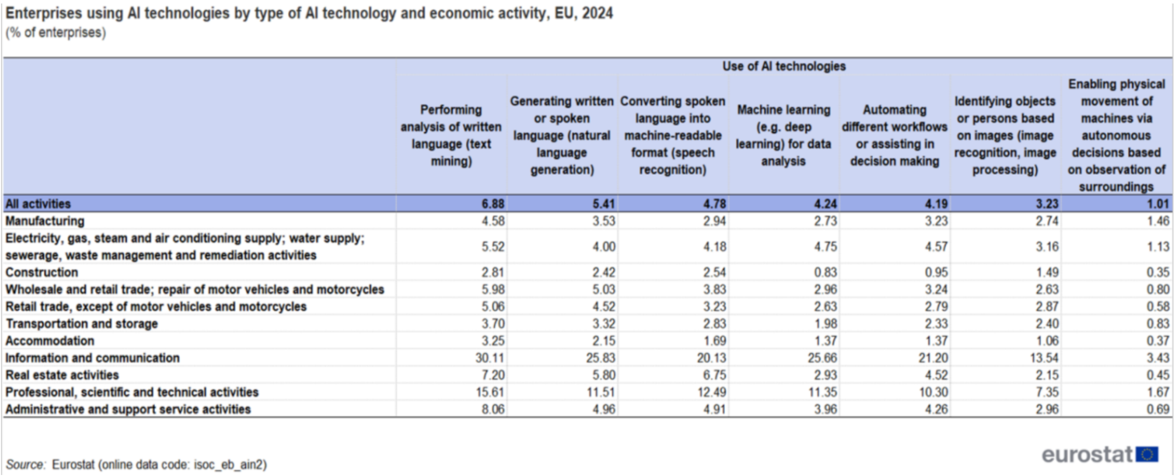


Figure 7-4 Enterprises using AI by economic activity (Eurostat, 2025)



Enterprises using AI technologies by type of AI technology and economic activity, EU, 2024
(% of enterprises)

	Use of AI technologies						
	Performing analysis of written language (text mining)	Generating written or spoken language (natural language generation)	Converting spoken language into machine-readable format (speech recognition)	Machine learning (e.g. deep learning) for data analysis	Automating different workflows or assisting in decision making	Identifying objects or persons based on images (image recognition, image processing)	Enabling physical movement of machines via autonomous decisions based on observation of surroundings
All activities	**6.88**	**5.41**	**4.78**	**4.24**	**4.19**	**3.23**	**1.01**
Manufacturing	4.58	3.53	2.94	2.73	3.23	2.74	1.46
Electricity, gas, steam and air conditioning supply; water supply; sewerage, waste management and remediation activities	5.52	4.00	4.18	4.75	4.57	3.16	1.13
Construction	2.81	2.42	2.54	0.83	0.95	1.49	0.35
Wholesale and retail trade; repair of motor vehicles and motorcycles	5.98	5.03	3.83	2.96	3.24	2.63	0.80
Retail trade, except of motor vehicles and motorcycles	5.06	4.52	3.23	2.63	2.79	2.87	0.58
Transportation and storage	3.70	3.32	2.83	1.98	2.33	2.40	0.83
Accommodation	3.25	2.15	1.69	1.37	1.37	1.06	0.37
Information and communication	30.11	25.83	20.13	25.66	21.20	13.54	3.43
Real estate activities	7.20	5.80	6.75	2.93	4.52	2.15	0.45
Professional, scientific and technical activities	15.61	11.51	12.49	11.35	10.30	7.35	1.67
Administrative and support service activities	8.06	4.96	4.91	3.96	4.26	2.96	0.69

Source: Eurostat (online data code: isoc_eb_ain2)

eurostat

Figure 7-5 Enterprise use of AI by technology and economic activity (Eurostat, 2025)

Policy makers should explore ways to support the digitalisation vision in the regulatory and educational framework. Helping businesses and educational institutions further the strategic autonomy and capabilities will empower the future workforce and support an independent, resilient, competitive, and productive Finnish and EU society.

7.3 European strategy for digital sovereignty

The EU’s approach to enhancing digital capabilities within the industry plans a coordinated effort to combine funding and financial instruments, reform educational and regulatory frameworks, and increase digital skills across society to drive innovation and competitiveness.

The Digital Education Action Plan (2021-2027) (European Commission, 2023) was launched to support the adaptation of educational and training services of all member states. It prioritises the “development of a high-performing digital education ecosystem” (European Commission, 2023), and the enhancement of digital skills and competencies by setting up a European Digital Education Hub to strengthen cooperation and exchange. The Digital Europe Program (DIGITAL) (European Commission, 2023) will target funding to reinforce the EU’s digital capabilities, aiming to enhance advanced digital skills by implementing specialised educational programs to achieve the “Digital Decade policy target of 20 million ICT experts in the EU by 2030” (European Commission, 2023) including. This includes reskilling and upskilling of the workforce. It is possible that funding the current Finnish government planned could be offset by direct European funding. Universities and universities of applied sciences ought to explore this possibility. At a societal level, the “European Skills Agenda” and the “Digital Education Action Plan” seek to ensure that 70% of the adult population has basic digital skills by 2025 and target a reduction by half of the underperforming digital skills in high school students across Europe by 2030. Under the “Connecting Europe Facility Program,” the “Digital Skills and Jobs Platform” aims to offer training and funding opportunities, information, and other resources on digital skills.

Other calls under the Horizon Europe program aim to foster digital skills and literacy. Horizon Europe recommends developing training material to provide the workforce with the right skillset to support the deployment of innovative products, processes, and services. It aims to have scalable, tested material that could potentially be “scaled up” through the European Social Fund Plus (ESF+)[12] to help close skill gaps. Horizon Europe proposes that special care should be put in cooperation of already existing initiatives, seeking collaboration with other relevant European, national or regional initiatives (European Commission, 2024) such as the European Institute of Innovation and Technology (EIT), the European Raw Materials Skills Academy and the Engineers for Europe (E4E) project.

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[12] European Social Fund Plus (ESF+) The ESF+ is a funding instrument to upscale training.

To meet future industry demands, the “Engineers for Europe” association recommends that European engineering education evolve in line with three main steps, aligning with earlier research findings. E4E emphasise the need for curriculum modernisation, industrial collaboration, and the promotion of lifelong learning. Specifically, states that universities and technical schools, in partnership with industry, should “regularly update and reform curricula to keep pace with technological advancements” and highlights the importance of companies "upskilling their current workforce to address the challenges of digital transformation," encouraging engineers to “engage in continuous learning through conferences, workshops, and training programs.” (Engineers for Europe, 2021).

8 The abstraction proposal

In a knowledge society, abstracting concepts and ideas is pivotal in simplifying complex processes and systems, making them easier to understand and manage. This simplification is crucial for improving productivity, streamlining operations and processes, and driving innovation across various industries. Abstraction enhances efficiency and effectiveness by enabling better decision-making and helping communication among stakeholders. Digitalisation abstracts engineering principles so that "atoms become bytes.” It turns "concepts into data” so that "data can turn into things.”

Computational thinking’s four tenets are: Decomposition, abstraction, algorithmic thinking, and pattern recognition. Decomposition involves sub-dividing complex problems into smaller manageable parts. By addressing these sub-problems individually, engineers can simplify complexity and apply focused expertise on each component. A “divide et impera” approach allows for a more systematic and efficient way of tackling engineering challenges. Abstraction is the process of generalising and then focusing on essential information, ignoring irrelevant details to make a problem more understandable and manageable, allowing engineers to develop effective solutions by focusing only on the most critical aspects. Algorithmic thinking involves developing step-by-step sets of rules to solve problems. This requires logical reasoning and the capability to sequence actions for a desired outcome. This ability is critical for developing systematic, replicable solutions in engineering. Finally, pattern recognition helps finding similarities and differences, trends, and voids of information to, from experience, apply practical solutions to new problems, saving time and effort while increasing solution reliability.

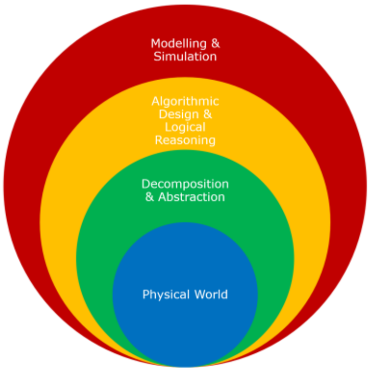


Figure 8-1 Abstraction of the engineering process

Teaching computational thinking to civil and structural engineering graduate students goes beyond teaching them how to code. While programming is a practical tool in an engineer's belt, computational thinking at its core is in developing an algorithmic mindset that enables engineers to break down, model and solve complex engineering problems in a "computer friendly" structured manner. It is a way to implement engineering ideas from paper to code.

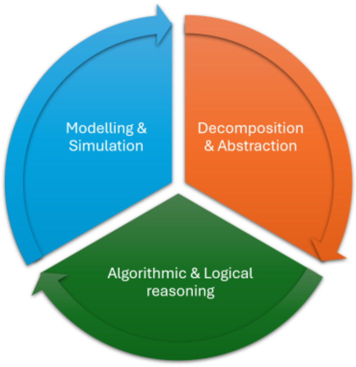


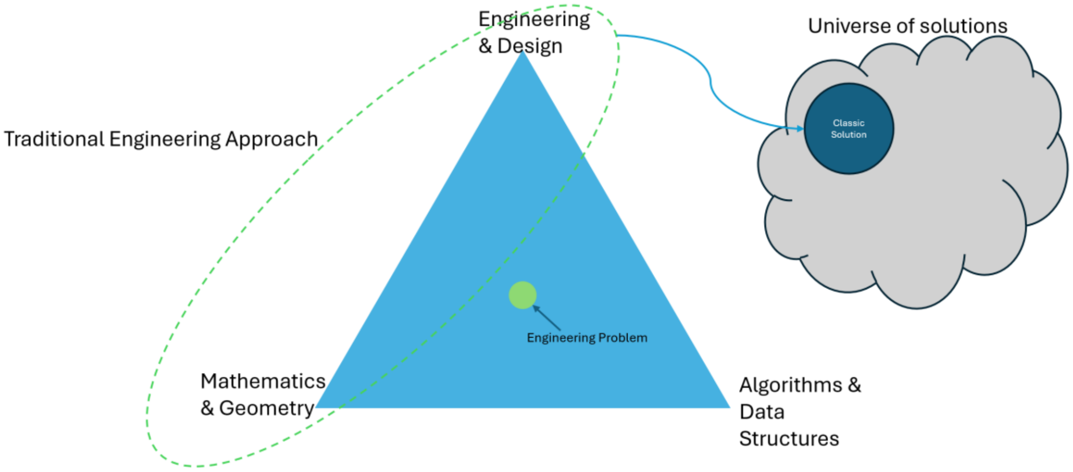
Figure 8-2 Tenets applied to engineering problem solving

8.1 Ideas to bits to atoms

The abstracted principles can help us understand the skills needed for an engineer to build a digital concept of a building. Engineers design physical buildings using principles of physics, material science and mechanics and codify those laws into human and mathematical language. The next consequent step in abstracted digitalisation, transforms those laws using computational geometry, programming algorithms and code into the language of computers to design, simulate and optimise physical processes and material atoms virtually, enhancing efficiency, innovation, and precision in their designs.

	Physical Building	*Digital Model*
Background	Engineering Principles	Computational Principles
Knowledge and Skills	• Physics • Material science • Structural engineering	• Algorithms • Data structures • Computational geometry
Techniques and procedures	• Construction techniques • Regulations and safety procedures • Dimensioning and optimisation	• Programming • Data analysis • Computational design
Tools and materials	• Blueprints and documents • Steel, nuts, bolts, concrete, rebar… • Prototypes, scale models and lab testing	• BIM, CAD, GIS • Code, coding languages and paradigms • Simulation and optimisation
Smallest unit of matter	Atom	Bit

In traditional engineering, physics, material science, and structural engineering principles are the foundation for designing and constructing reliable structures. These principles guide how forces, materials, and elements such as columns and beams interact. In the digital world, engineers rely on computational algorithms, data structures and computational geometry to simulate, analyse and optimise complex scenarios.



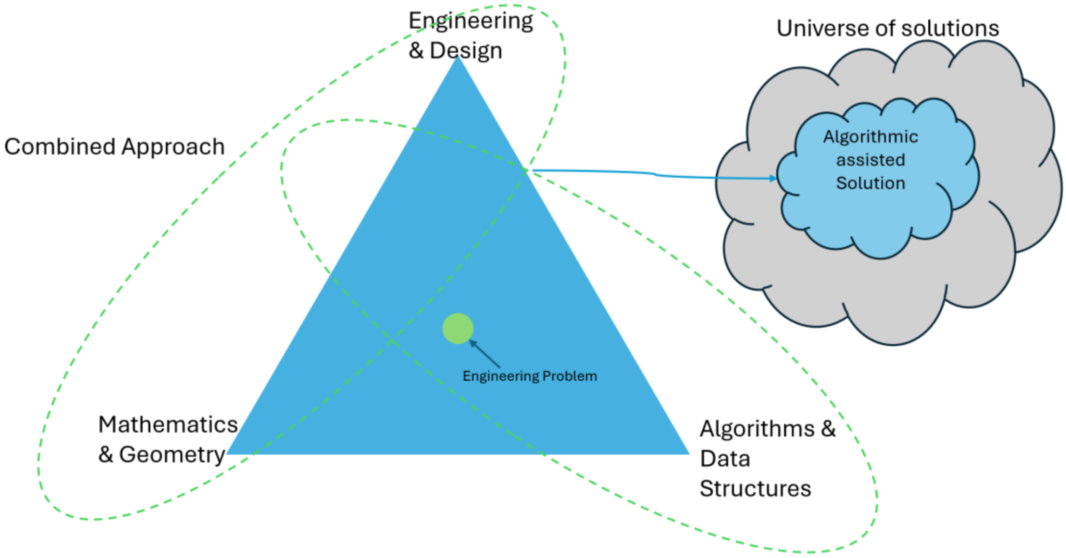


Figure 8-3 Adapted from Algorithmic Assisted Modelling by Jaakko Arokoski. Tampere University

Both realms require a rigorous problem-solving approach and understanding of constraints and limitations to ensure safety, correctness and functionality expressed through different methodologies. While mathematical foundations remain the same, the emphasis shifts from direct physical manipulation to an abstract representation of the same phenomena. Traditional engineering curricula also focus on regulations, safety procedures and dimensioning techniques to ensure that structures meet performance and legal standards. In the digital domain, engineers still need to understand how to size beams and how to adhere to building codes and can codify these rules, writing scripts, automating tasks, and using parametric modelling tools. The interaction between physical knowledge and digital proficiency accelerates the design process, enriches it and allows engineers to evaluate multiple iterations under different conditions, gathering data and integrating them into actionable information. Construction techniques, the tangible side of engineering, transform blueprints and plans into finished structures. On the digital side, engineers use BIM, CAD, GIS to assemble virtual models containing geometrical data and metadata that defines building components and allow for a replication of sequences and material behaviour. The digital version allows for a replicated "digital twin" of real phenomena in a virtual, close to cost-free environment. Plans can now be shared and changed, fostering collaboration, streamlining revision processes, and integrating data and decisions that otherwise would be difficult or impossible to share. At the most fundamental level, traditional engineering deals with cinder blocks, steel beams and wooden panels, atoms, the physical building blocks of matter. In the digital engineering analogy, the basic unit of matter, the bit, encodes and builds up the information representing those structures. By translating behaviour from atoms to bits, engineers gain flexibility and speed at a "too cheap to meter" replication cost. Moreover, in the process, the engineer has gained a deeper understanding of the engineering concepts by focusing on the logical description of the engineering process, akin to what in software engineering is called "rubber-ducking," a method to solve programming failures, bugs, by describing the problem in natural language to a "toy duck." The experience is that of teaching by explaining a problem or concept to someone else and finding the solution through the process of explaining the problem by considering different approaches to the question. Learning to teach computers and themselves. Computational thinking can also be an "unplugged" activity, not involving computers and particularly useful in introductory courses to establish conceptual understanding.

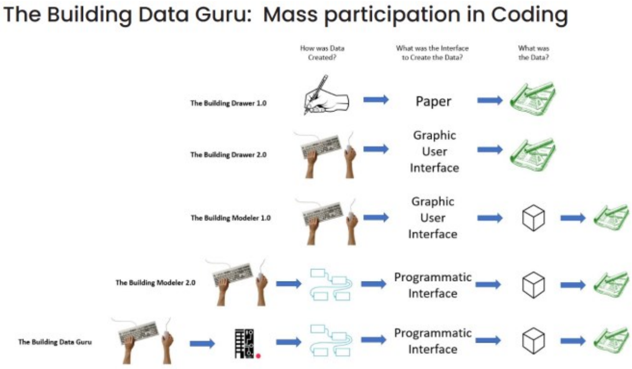


Figure 8-4 Computational approach to engineering (source: (Piermarini, 2019))

Recognising these foundational elements becomes necessary for "classical" engineers to bridge the gap between traditional and digital methodologies, to remain competitive and capable of understanding and predicting the outcomes of their actions and decisions.

8.2 Why it matters

Traditional engineering problems are inherently abstract, complex mathematical representations of stress, strain, and load distributions etc., in the real world, helping engineers to identify patterns, test hypotheses, and iterate over solutions more effectively, leading safer and better optimised designs, producing better decision-making information and facilitating decision taking. Engineers trained in computational thinking can more effectively resolve, innovate, and implement solutions by seamlessly integrating models and digital simulation closing the gap between abstract theoretical models and their practical applications, ensuring they are prepared to meet the challenges of the engineering world.

Abstraction is crucial as it enables scalability, interoperability automation and optimisation. It allows for data-driven feedback, transforming engineering task production, by converting physical processes and parameters into code and data structures. Abstraction supports automation and optimisation by embedding engineering knowledge into scripts and models, freeing up time for creative problem-solving, that finally can be fed back into the system and digital model to learn from, closing the loop between design, construction, and operation.

Even further, if engineers address digitalisation by simply buying licenses or services, they risk reducing their role to that of technicians operating black-box tools (Talaat;Kohail;& Ahmed, 2022), without truly understanding the underlying mechanisms. This superficial engagement undermines the engineer’s ability to understand, innovate and master their profession, leaving them vulnerable to an ever-evolving digital landscape. Engineers who rely on tools they cannot manipulate or create independently, relinquish the critical insights needed for creative problem-solving and adaptive design. Such dependence will eventually sideline engineers, making them worse professionals and less influential in shaping their field. Failing to embrace and master advanced digital skills, engineers face the danger of becoming outdated, dependable and irrelevant in an increasingly digital world. More critically so, in the case of AI tools.

9 Professional survey and interviews

A set of interviews and a survey (Appendix A2) were conducted to study the potential integration of computational thinking and skills in engineering courses.

9.1 Professional survey

A survey was created and promoted through a professional channel on LinkedIn. As expected, the total number of responses was limited, but confirmed previous independent research.

The survey had 19 respondents, from various engineering disciplines, with strong representation in structural engineering (6 responses) and significant participation from civil, road and highway and transport or traffic engineering. The experience level was generally in the mid-career range, with 11 to 20 years of experience being the largest group represented and most holding senior or managerial positions suggesting these insights come from seasoned professionals with real-world experience. Predominantly, respondents practiced in the EU/UK region (15), with a majority, 75%, having graduated in Finland with studies ranging from bachelor's to master's degrees. A not-so-striking finding was that very few respondents felt their education fully prepared them for the digital transformation of the AEC industry, with 44% of the respondents describing their preparation as "minimally prepared" and 28% as "not prepared at all." Although subjects like BIM, GIS and mathematical computation were included in their studies, many core subjects for computational skills like programming fundamentals, algorithms, and others were either minimally covered or missing. An overwhelming majority would have liked to learn more programming and computer-science-related subjects in their studies, and they believe engineering curricula should significantly expand these topics or even create specialisations that merge traditional AEC subjects with digital and computational training.

Given the perceived shortcomings in their formal education, 61% of the professionals have taken the initiative to self-train, mostly independently through online courses rather than in structured or employer-provided programs. While added self-training was "somewhat effective," it has not fully closed the gaps. About half of the respondents had received "some form" of computational training through their employers. Yet, many feel that their employers are only “somewhat prepared” to support digitalisation, with a substantial number relying on prebuilt software tools, indicating that integrating custom solutions and skills into workflows is challenging. Insufficient employer or management support, lack of resources, and resistance to change were identified as the main barriers to adoption. Difficulty integrating them into current workflows was also named by the respondents that point out that better financial backing, training, policy changes, and leadership support, is needed.

Between the respondents, there is a clear consensus (89%) that computational competencies are important today and will be critical in the next 5 to 10 years, with most respondents rating them as “important” or “very important” for current and future professional needs. Foundational skills in algorithms, scripting and computational design are believed to be crucial to machine learning and advanced computational design to a lesser extent. Survey participants provided key recommendations for educational institutions:

- Integrate formal computational skills such as programming into the curriculum.
- Enhance practical training with real-world cases or hands-on projects for BIM, GIS, and visual programming and algorithmic-assisted design.
- Consider developing dedicated interdisciplinary courses or specialised programs that blend traditional engineering with modern computational competencies.

In conclusion, the survey indicates professionals recognise a significant gap between traditional engineering education and the digital skills required for today’s and future AEC industry. While 83% of the respondents tried to bridge the knowledge gap on their own, there is a strong call for academia and employers to invest more in training to future-proof the industry as digitalisation continues to reshape how engineering is done. There is a need for a coordinated effort between educational institutions, government, and firms to update training programs to keep pace with technological advancements.

9.2 Interviews

Interview excerpts have been lightly edited for clarity and readability, to remove verbal fillers and repetitions while preserving the original meaning. Interviews were also summarised for brevity.

9.2.1 From a policy point of view

Interview with Saku Lehtinen, educational policy expert from The Confederation of Finnish Construction Industries (CFCI) (Rakennusteollisuus RT - Finland).

The discussion centred on the critical need for digital skills within the construction industry and the essential steps needed in terms of education for current and future engineers to meet those demands. Lehtinen acknowledges this as a “hot topic,” particularly when thinking about the pervasive influence of AI, but clarifies that the issue encompasses a broader issue than AI. On the necessity of digital skills, Lehtinen states, “I agree very much with the need for these skills. In general, you must have some basic understanding, not just engineers, but also blue-collar employees” and elaborated that while the level of expertise might vary, both consultants and designers whom his organisation represents, as well as construction engineers, require some fundamental understanding of it. On current initiatives for enhancing computational skill development in engineering curricula, Lehtinen admits his organisation does not yet have a specific clear message. He attributed rapid technological advancements as challenges to setting up fixed requirements that could quickly become obsolete. However, he points out that in Finland’s secondary vocational education level, a “sort of reform for competencies” is underway to incorporate basic digital and green transition skills nationwide.

Concerning necessary policy changes in education, Lehtinen suggested that while universities and universities of applied sciences in Finland have considerable autonomy in designing their programs, he observed that universities currently offer “very little digital capabilities,” and that most universities of applied sciences lack substantial offerings in this area, with Metropolia UAS being a notable exception. While the Ministry of Education and Culture cannot directly mandate curriculum changes, Lehtinen implied that a strong, unified message from the industry regarding the importance of digital skills would likely influence their considerations. Lehtinen agrees on the essential role of collaboration between industry and academia to ensure relevance and currency of educational curricula with technical progress. In discussing the direction of computational skill development, Lehtinen suggested that foundational engineering education should incorporate basic digital literacy and that master's level programs should offer avenues for specialisation in emerging technologies.

Looking ahead, Lehtinen envisions that improved computational competencies could fundamentally reshape the AEC industry, offering significant opportunities and boosting overall productivity. He underscores the persistent issue of low productivity in the construction sector, stating, "There have been no positive signs during the whole last century, and we are behind when compared to other industries, so to turn it around, we need to do something new, something different."

About the responsibility for upskilling professional employees in the AEC industry, Lehtinen argues it must be a collective effort shared among "all three parties, the individual itself, the employer and society." He noted that for highly specialised skills the onus typically falls in the employer and employee, however, Lehtinen stressed the importance of foundational level digital skills, that integrated into engineering education would facilitate subsequent specialisation and adaptation to new technologies. Lehtinen advocated for "avoiding educational leaves for upskilling," suggesting upskilling should be integrated with ongoing work or pursued privately.

On policy beyond the Ministry of Education and Culture, Lehtinen acknowledged the feasibility of other ministries, such as the Ministry of the Environment, potentially enforcing competency requirements for engineers working in specific knowledge areas. However, the extent of such influence was difficult to predict.

Finally, Lehtinen highlighted two primary reasons for the critical importance of addressing the digital skills gap: Finland's ageing population and declining birth rate, which necessitates leveraging technology to compensate for a shrinking workforce, and the long-standing stagnation in productivity in the industry, citing a recent thesis indicating that "about 80% of the time in the construction site is unproductive" (Görsch, 2024). While acknowledging potential resistance to automation driven by job security concerns, he suggests that technology and innovation could automate repetitive and hazardous tasks and help reduce rising construction costs, overcome language barriers and facilitate communication concerning the increasing presence of foreign labour in Finnish construction, deliver optimised solutions and potentially save time money and effort.

9.2.2 From a professional point of view

Interview with Petri Kortelainen, computational design manager at RBU Automation, Ramboll, Finland.

The discussion centred around ideas on integrating computational methods in engineering degrees. Kortelainen initially stated that, based on his understanding, universities already have a full curriculum and might not be willing or capable to add extra courses. He suggests that “to get anything computation related into the curriculum, I would say that it cannot be separate courses but during the engineering courses themselves.” Kortelainen acknowledges that this approach would “require quite a lot from the teacher” and might need preliminary knowledge like basic programming. However, this integration could enhance the teaching process by making it more visual and interactive. He mentions, for example, that if one makes statics calculations with a computer model students could “play around with the parameters and see what the effect of any change is, yielding a more intuitive feeling of what is underlying behind the numbers.” He found traditional pen-and-paper statics classes unhelpful, stating “it was awful and learned nothing really from the university statics classes.” Kortelainen considered that every civil and structural engineer should have “some level of computational design capability.” He also raised the concern that the increasing reliance on software without an understanding of its inner workings. As an example, he points out that FEM analysis, often included in engineering degrees, yet engineers “do not really go into how the computation happens. So, we are using them, learning how to interpret the data they produce, but we do not know how they work.” Looking towards the future and the impact of AI, Kortelainen believes that utilising future models will require “at least some basic knowledge of how the computation works,” and while AEC engineers might not need to code extensively, “computational thinking is the key because if you can take apart your problem into smaller bits, you can explain the problem.” He also considers the possibility of having specialists like computer scientists assist when handling more complex problems and systems. However, he acknowledges the gap between the fields is large and that we would need to “try and join them from both sides.” Finally, he reiterated the potential of computational design to enhance the learning process by allowing students to “do a million calculations, visualise the results and get an idea of how the engineering works. In the real world, you rarely do calculations by hand.”

9.2.3 From an educational point of view

Q&A Interview with Professor Kirsi Virrantaus, vice-Dean of the Aalto School of Engineering, Finland.

How do you view the overall role of computer science courses in “classical engineering” curricula, especially as digitalisation transforms the AEC industry?

I think it is of utmost importance that engineering students learn at least the specialities of computer-aided engineering. It requires basic courses on programming, data structures and data management as well as the basics of computer graphics, visualisation, and AI.

How can computational skills and techniques complement and enhance the traditional engineering methodologies taught in core engineering programs?

Typically, the courses include only references to engineering software packages but if the students do not have CS skills, they may be able to use these packages, but they have no idea about their usefulness to a specified problem. They might use the wrong tools.

Would more CS courses obligatory for “classical engineering” degrees, better prepare students for the evolving demands of the industry?

Yes.

What potential challenges might institutions face in implementing such changes?

Most of the CS courses do not "fit" to the engineering program structure and it is too much work for the teachers to implement applied courses. I had 5 applied courses and a full minor in our school but when I retired nobody was able or willing to continue and the whole minor was cancelled.

9.2.4 From a student's point of view

Q&A Interview with Alex Laitinen civil and structural engineering student who participated in the computational course and currently is doing a professional internship at a large engineering firm.

Which digital tool from your studies did you end up using during your work practice?

During my work practice I used the visual programming tool Grasshopper/Rhino which was fairly manageable to get into since I had learned the basics during the elective course "Introduction to Computational design" in which we used the similar tool, Dynamo for Revit. Other tools from my studies that I also used during my work practice were Tekla and to a lesser extent, AutoCAD.

Did you notice any benefits from applying a computational approach to your tasks?

Tasks get easier since the computational approach gives you more room for more effortless and faster adjustments, and the possibility to create more complex and finer designs than would be possible with, for example, traditional modelling.

Was there a digital skill you felt you could have used more or learned in more depth?

It would have been interesting to get a wider grasp of different Grasshopper plugins like the Tekla plugin for example. Forming a better understanding of FEM-tools like Sofistik and getting a greater insight into coding would have been useful as well.

How useful do you think it would be to have more computational courses in your curriculum?

It's a necessity since it's the skillset of the future. From what I have gathered during my work practice, I think that to be a competitive engineer in the future, you need to know and be able to work with a wide variety of computational design tools.

What simple digital change do you think could have a big impact on engineering in the near future?

A broader switch to and incorporation of different computational design tools, as well as AI plugins for traditional design tools will in my opinion bring a big change.

Anything else you would want to add? You are free to say anything you feel regarding the topic or nothing at all.

It is surprising that computational design courses haven't been included in the curriculum, since the time to learn these skills is now, to keep up with the industry changes.

9.2.5 From a business leadership point of view

Interview with Max Levander, Chief Technology Officer (CTO) for A-Insinöörit (AINS Group), Finland.

The conversation centred on the role of computational competencies for engineers and a computational approach to engineering. Levander emphasised the importance of computational competencies, indicating that fundamental skills such as scripting and computational thinking should be integrated early in an engineer's educational journey as a foundational step for future proficiency. He used the following analogy, "it's like learning to read; nobody at age 10 is a master reader, but if you know the alphabet, you can develop and grow as a reader" and expressed concern about the current state of computational skills development, observing that new engineering graduates often lacked these skills and stated, "You cannot assume new students will have skills in coding or graphical scripting; the industry average indicates otherwise."

Regarding specific computational competencies he argued that "No-code and low-code platforms are a really good place to start. From these, it's not a long way to Python, which enables you to implement artificial intelligence and other project-specific solutions." Levander also brought forward the importance of understanding relational databases, describing them as "valuable for supporting the overarching theme of computational thinking" as it offers a "multidimensional approach to managing data."

On the topic of training and upskilling initiatives, Levander noted that the industry faced challenges, particularly around perceived return on investment (ROI) and the immediate applicability of these skills in a corporate environment, and highlighted the joint responsibility of academia, industry, and individual engineers in fostering a culture of continuous learning. "It's paramount for universities to teach computational fundamentals. Still, businesses must view upskilling as a profitable investment, leveraging these skills to enhance revenue and efficiency." Levander further discussed barriers to comprehensive training policy adoption, acknowledging that traditional business models focused primarily on profitability could hinder investment in computational training. He explained, "The legal objective of a company is to drive profit” and pointed out that the predominant contract methods in the industry could disincentivise automation due to a “potential loss of billable hours in hourly-based contracts, while in fixed-price contracts it could lead to inefficiencies as tasks tend to expand to fill allotted time.” Despite this he felt his “gut feeling” was that engineers proficient in computational skills, tended to perform better overall, even in traditional engineering tasks, suggesting a correlation between computational literacy and general engineering capability.

On incentivising continuous education among engineers, Levander brought up successful models such as specialised certifications (e.g., FISE certifications), emphasising that a linkage between such qualifications and business performance could act as motivators for companies and employees alike.

Looking forward over the next decade, Levander predicted that AI advancements could substantially accelerate digitalisation within the sector, potentially transforming engineering firms into technology solution providers and predicted that assuming an optimistic scenario and as AI technology matured, “the business model of selling hours could become obsolete, replaced by solution-focused, data-driven models offering greater quality and efficiency.”

Overall, Levander called for a collaborative effort involving educational institutions, industry leaders, and policymakers to advance computational skills in engineering, acknowledging current gaps and highlighting opportunities for innovation and enhanced productivity within the sector.

10 Course and results

An introductory course that would serve as a foundation for computational thinking and algorithmic design for engineering students was planned and offered during the academic year 2024-2025 at Novia UAS. The course emphasised breaking down complex engineering problems, abstracting essential engineering fundamentals and applying algorithms and programming to teach future graduates how computational methods can be applied to real-world engineering challenges and projects.

10.1 Course objectives

The hands-on lectures had the following objectives:

- Design and analyse algorithms using flowcharts and pseudocode.
- Development of basic linear algebra, vector mathematics and computational geometry knowledge.
- Develop basic programming skills and concepts using Python.
- Understanding the application of computational thinking principles in an engineering context.
- Breaking down complex engineering problems into manageable components.
- Simulation and data analysis of simplified real-world engineering problems using Revit Dynamo and PowerBI.

10.2 Adopted methodology

A two-credit elective course was offered to third- and fourth-year civil and structural engineering students, equivalent to 54 hours of work over six practical lectures. A total of fourteen students took part in the lectures. The lectures focused on building the required skills needed to decompose engineering problems into workflows that would then be interpreted into computer language. Coding skills were added incrementally every week, resulting in two final lectures where the gained knowledge was used to solve an engineering problem computationally. Attendance was obligatory, but no obligatory assignments were introduced to evaluate real interest in the subjects taught. By the end of the six weeks course, 28% of the students showed enough interest and had created computational solutions for other engineering courses.

10.3 Course content

The content created as self-explanatory lectures using “Jupyter Notebooks,” allowed to include detailed explained content and executable code. The course included the same computational problem-solving concepts from a programmatical point of view and a low-code approach using Dynamo for Revit. The programming language was Python and the course was divided into three sections:

1. **Applied principles of programming**: Dealing with the basic programming concepts and algorithmic principles, and the basics of Python syntax.

2. **Applied principles of computational geometry**: Dealing with basic vector mathematics and linear algebra principles as well as concepts of computed geometry.

3. **Applied algorithmic assisted design and computational problem solving**: Dealing with applying computational thinking and skills to solve basic structural engineering problems, engineering optimisation, and basic data science principles.

In this last section students were introduced to the abstraction principle, central tenet discussed earlier in this thesis, which involves decomposing problems into more manageable tasks. In this section, students were guided through the process to effectively break down a well-known structural engineering problem for third- and fourth-year students into discrete steps that could be easily algorithmically described and computed.

The students then proceeded to simulate multiple scenarios and evaluated the results of the simulation by programmatically extracting values, graphing them and applying their structural engineering knowledge to critically evaluate and obtain an optimised solution. This last step reinforced the practical application of computational thinking and algorithmic and programming skills for solving real-world problems and developing innovative solutions. The whole course is available on GitHub (Romero, Introduction to Computational Design for Structural Engineers, 2025) under a permissive license free for download[13].

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[13] Code is available from the GitHub repository.

10.4 Results

After the course, the students completed a survey (Appendix A1) to evaluate their thoughts and potential ways forward to implement such a course in the studies. The survey revealed that most participants entered the course with little or no previous knowledge or limited exposure to computational methods and programming (79%). 64% positively shifted their perspective towards the inclusion of this kind of course, never-the-less 36% of the students, did not see computation as significant in their future tasks and career. By the end of the course, most students acknowledged the role of these skills in structural engineering when tied to discipline-relevant topics[14]. Overwhelmingly, students supported the idea of integrating computational thinking in the curriculum through modular, sequential courses, with 50% preferring short three credit courses while 42% would prefer longer five credit courses. This might not necessarily be an attitude towards computational teaching but how students prefer learning. A couple of the students commented that two credits were too little to go over all the material at a reasonable pace.

A strong preference for hands-on learning supported by tutoring was expressed, and a clear demand for a practical, supportive framework that would prepare them for the evolving demands in their future careers, showing that while lectures remain important, experimental learning and direct application of computational concepts is valuable. When asked about the reason behind their thoughts for including this type of course, 78% of the respondents thought it would improve their job prospects after graduation and 85% that it could open new career paths. A minority did express concerns about focusing effort away from fundamental principles or the learning curve.

The main takeaway from survey for designing future computational thinking engineering courses for engineering bachelor’s students in Finland is:

- **Limited prior exposure (79%)**: No such thing as digital natives. Most students are newcomers to computing and programming, highlighting the need for introductory-level courses.

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[14] Note: The professional experience of the students is limited.

- **Curriculum preference (64%)**: The survey shows broad support for inclusion, ideally structured as sequential courses.
- **Contextualisation**: Students were more receptive to programming activities directly relevant to their engineering discipline.
- **Teaching and support**: Effective learning depends on hands-on, accessible courses with real-world examples, mentoring and technical support.

The statistical significance of this study is limited given sample is small. The 14 respondents (100% of the participants) correspond to approximately to 31% of the student pool. This limited sample size restricts the analysis and may introduce sampling biases that affect the study. None of the results had an overwhelming majority, except for lack or limited previous exposure to computational methods. Also, participation was voluntary, and respondents might have had a predisposition to the subject skewing the results. Consequently, while the results offer insight into student attitudes towards computational skills in engineering, they should be interpreted with caution. Then again, the research goal was not statistical significance, but to gather general attitudes to the subject and create a framework to build upon.

On the other hand, the results fall in line with previous research, describing that despite some initial resistance arising from the notion that computer programming is not a relevant skill (Bettin;Jarvie-Eggart;Steelman;& Wallace, 2021), that there is a trend of increased student demand for computing courses (McCord, ym., 2024) and that students are more likely “to buy in to” courses when concepts are directly tied to engineering applications (Lane & Hawkins, 2024) as it provides students of clear links between “coding skills and potential real-world application.” The study also found support for the finding that many engineering students have none or limited prior programming skills as describe in (Cao;Lim;Dale;& Tasler, 2021).

11 Recommendations for implementation

Digital transformation will reshape the future of engineering education and require curricular updates that integrate digital and computing technologies and skills. For that, this thesis proposes the following **IMPEL** strategy, a summary of the recommendations for universities and universities of applied sciences wanting to implement computational thinking and courses in their curriculum.

impel

(ɪmˈpɛl)

verb

Word forms: -pels, -pelling, -pelled

(*transitive*)

1. to urge or force (a person) to an action; constrain or motivate
2. to push, drive, or force into motion

Collins English Dictionary. Copyright © HarperCollins Publishers

Figure 11-1 Impel: To push, drive or force into motion

- **Integrate**: Programming, algorithms, automation, numerical computing and simulation, data management and analytics into strategically chosen foundational mathematics, engineering, and science courses.

- **Modularise**: Offer flexible and agile study paths with courses, workshops, and collaboration internships to respond to evolving digitalisation demands.

- **Personalise**: Provide a data-driven learning experience using advanced technologies such as LLMs, virtualised and asynchronous adaptive learning environments etc., to offer personalised guidance, immediate feedback etc.

- **Enhance**: Revise curricular programs to include computational thinking, programming fundamentals and algorithmic design, which will serve as foundation for abstracting and solving complex engineering problems.

- **Lead**: Invest in faculty development, provide educators with training and resources to impart these skills. Foster collaboration and interdisciplinary projects between engineering, computer science and data experts.

The following recommendations can be used as a starting point based on the research results.

- Introductory programming and algorithmic thinking courses in Python as early as possible in the educational cycle.
- Integration or adaptation of a computational approach in engineering courses using scripting, visual programming, and other digital resources.
- More advanced programming, computing, and data science courses should be offered, later in the study cycle, to reinforce learning.

Considering that degree programs take years to develop and implement, it would be wise to develop trial implementations that would partially integrate the ideas presented into existing courses, evaluating what works in the short and long term, to evaluate the effectiveness of various strategies in the context of the specific university. Factors such as student enrolment trends, faculty training, available technological[15] and economic resources and long-term goals. It could be wise to share resources between technical faculties for enhanced efficiency. For example, basic computational thinking courses such as programming, algorithms, or data structures, could be compatible between disciplines. In the case of civil and structural engineering faculties, this could mean for example, that the programming course would target common courses like mechanics or physics. For faculties with natural sciences and engineering under the same roof, programming courses could target common goals, like mathematics and data science, using generalised examples[16].

11.1 Structural engineering case examples

The following is a list of simple examples directed towards integrating computational skills within civil and structural engineering undergraduate degrees in order of difficulty of implementation:

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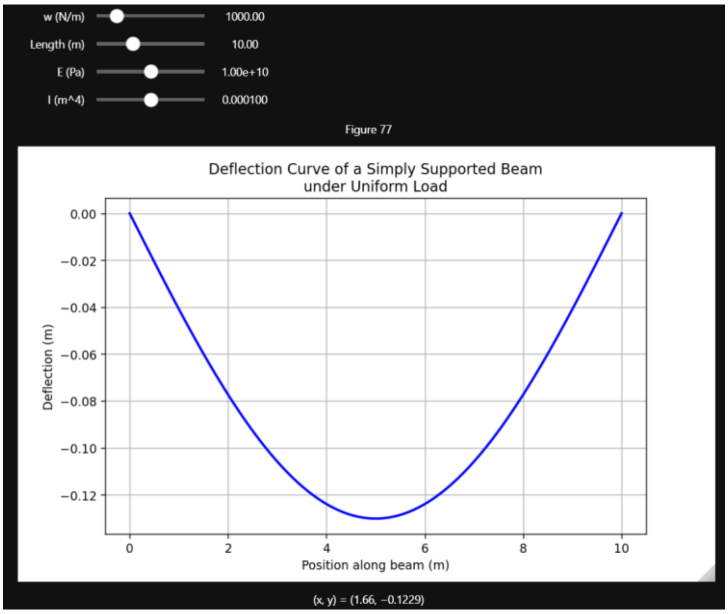
[15] Most technical faculties already own the minimum required in terms of technological resourcing, to start applying these recommendations.

[16] Even when this partly contradicts the findings of this research.

1. Interactive visualisation for a simply supported beam under uniform linear load (computed documents).
2. Interactive visualisation for the moment area of inertia for a rectangular plate with precalculated results and save functionality (computed exploration).
3. Computational search for the best-suited beam for a particular load case given a table of steel beams (computed optimisation).

The examples help the student link theoretical equations with real-world tasks, encouraging exploration. They also give students immediate feedback, reinforcing the knowledge of "parameter sensitivity," helping them develop a better intuition for how structural properties and systems change. The examples are simple enough that with little explanation, the computational skills needed become easy to understand. The code required for interactivity can be provided as a template for the student, who would only need to complete the calculation functionality[17].



w (N/m) 1000.00
Length (m) 10.00
E (Pa) 1.00e+10
I (m^4) 0.000100

(x, y) = (1.66, −0.1229)

Figure 11-2 Exercise 1

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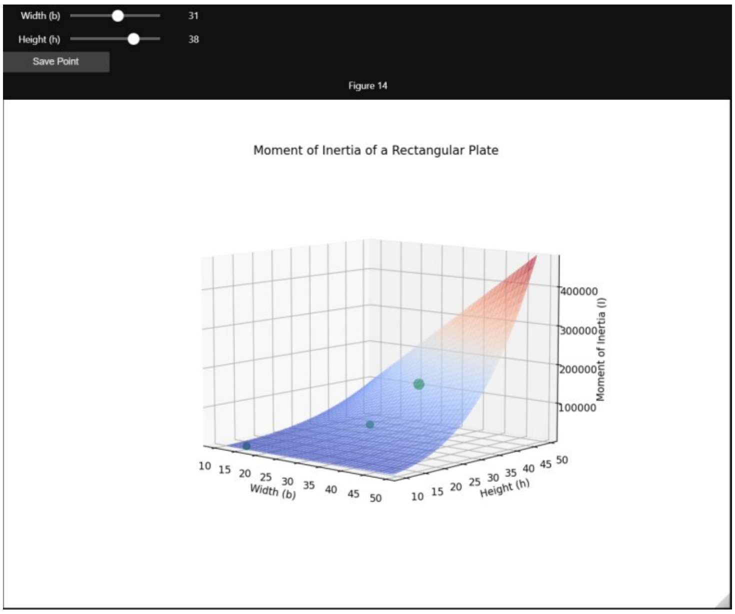
[17] All code is available on the Github repository.



Width (b) 31

Height (h) 38

Figure 11-3 Exercise 2

Examples could include the application of AI tools in the context of learning. For example, using Retrieval Augmented Generation (RAG) applications such as NotebookLM[18] to explore documents such as the Eurocode in different languages and country versions.[19] Also knowledge graph tools could be used to navigate the related information existing in different norms and codes.

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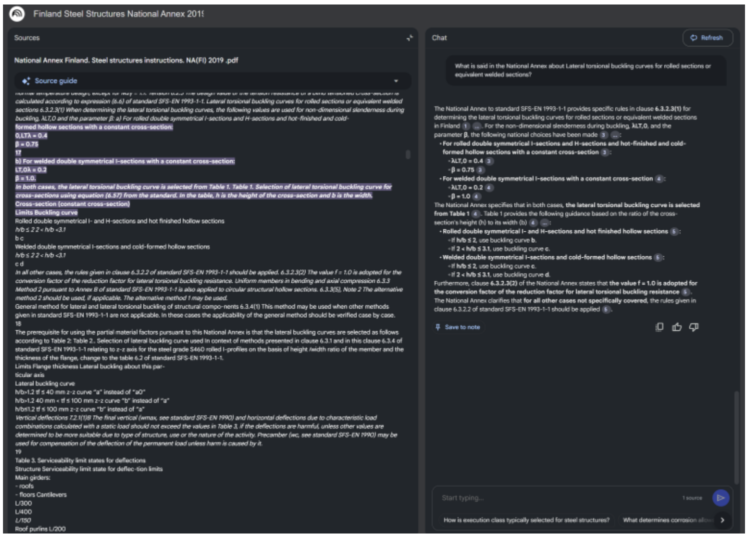
[18] https://www.notebooklm.google.com/

[19] This would need to be with done carefully, explaining the limitations of current AI tools and their applications. This use case is currently used in engineering firms to navigate national, local and technical documentation when designing engineering solutions in other nations, giving project engineers the possibility of finding specific engineering details that they might not be familiar with.



National Annex Finland. Steel structures instructions. NA(FI) 2019 .pdf

calculated according to expression (6.6) of standard SFS-EN 1993-1-1. Lateral torsional buckling curves for rolled sections or equivalent welded sections 6.3.2.3(1) When determining the lateral torsional buckling curves, the following values are used for non-dimensional slenderness during buckling, λLT,0 and the parameter β: a) For rolled double symmetrical I-sections and H-sections and hot-finished and cold-
formed hollow sections with a constant cross-section:
0,LTλ = 0.4
β = 0.75
17
b) For welded double symmetrical I-sections with a constant cross-section:
LT,0λ = 0.2
β = 1.0.
In both cases, the lateral torsional buckling curve is selected from Table 1. Table 1. Selection of lateral torsional buckling curve for cross-sections using equation (6.57) from the standard. In the table, h is the height of the cross-section and b is the width.
Cross-section (constant cross-section)
Limits Buckling curve
Rolled double symmetrical I- and H-sections and hot finished hollow sections
h/b ≤ 2 2 < h/b <3.1
b c
Welded double symmetrical I-sections and cold-formed hollow sections
h/b ≤ 2 2 < h/b <3.1
c d
In all other cases, the rules given in clause 6.3.2.2 of standard SFS-EN 1993-1-1 should be applied. 6.3.2.3(2) The value f = 1.0 is adopted for the conversion factor of the reduction factor for lateral torsional buckling resistance. Uniform members in bending and axial compression 6.3.3 Method 2 pursuant to Annex B of standard SFS-EN 1993-1-1 is also applied to circular structural hollow sections. 6.3.3(5), Note 2 The alternative method 2 should be used, if applicable. The alternative method 1 may be used.
General method for lateral and lateral torsional buckling of structural compo-nents 6.3.4(1) This method may be used when other methods given in standard SFS-EN 1993-1-1 are not applicable. In these cases the applicability of the general method should be verified case by case.
18
The prerequisite for using the partial material factors pursuant to this National Annex is that the lateral buckling curves are selected as follows according to Table 2: Table 2.. Selection of lateral buckling curve used in context of methods presented in clause 6.3.1 and in this clause 6.3.4 of standard SFS-EN 1993-1-1 relating to z-z axis for the steel grade S460 rolled I-profiles on the basis of height /width ratio of the member and the thickness of the flange, change to the table 6.2 of standard SFS-EN 1993-1-1.
Limits Flange thickness Lateral buckling about this par-
ticular axis
Lateral buckling curve
h/b>1.2 tf ≤ 40 mm z-z curve "a" instead of "a0"
h/b>1.2 40 mm < tf ≤ 100 mm z-z curve "b" instead of "a"
h/b≤1.2 tf ≤ 100 mm z-z curve "b" instead of "a"
Vertical deflections 7.2.1(1)B The final vertical (wmax, see standard SFS-EN 1990) and horizontal deflections due to characteristic load combinations calculated with a static load should not exceed the values in Table 3, if the deflections are harmful, unless other values are determined to be more suitable due to type of structure, use or the nature of the activity. Precamber (wc, see standard SFS-EN 1990) may be used for compensation of the deflection of the permanent load unless harm is caused by it.
19
Table 3. Serviceability limit states for deflections
Structure Serviceability limit state for deflec-tion limits
Main girders:
- roofs
- floors Cantilevers
L/300
L/400
L/150
Roof purlins L/200

What is said in the National Annex about Lateral torsional buckling curves for rolled sections or equivalent welded sections?

The National Annex to standard SFS-EN 1993-1-1 provides specific rules in clause **6.3.2.3(1)** for determining the lateral torsional buckling curves for rolled sections or equivalent welded sections in Finland ① .... For the non-dimensional slenderness during buckling, **λLT,0**, and the parameter **β**, the following national choices have been made ③ ...:

- **For rolled double symmetrical I-sections and H-sections and hot-finished and cold-formed hollow sections with a constant cross-section** ③:
  - **λLT,0 = 0.4** ③
  - **β = 0.75** ③
- **For welded double symmetrical I-sections with a constant cross-section** ④:
  - **λLT,0 = 0.2** ④
  - **β = 1.0** ④

The National Annex specifies that in both cases, **the lateral torsional buckling curve is selected from Table 1** ④. Table 1 provides the following guidance based on the ratio of the cross-section's height (h) to its width (b) ④ ...:

- **Rolled double symmetrical I- and H-sections and hot finished hollow sections** ⑤:
  - If **h/b ≤ 2**, use buckling curve **b**.
  - If **2 < h/b ≤ 3.1**, use buckling curve **c**.
- **Welded double symmetrical I-sections and cold-formed hollow sections** ⑤:
  - If **h/b ≤ 2**, use buckling curve **c**.
  - If **2 < h/b ≤ 3.1**, use buckling curve **d**.

Furthermore, clause **6.3.2.3(2)** of the National Annex states that **the value f = 1.0 is adopted for the conversion factor of the reduction factor for lateral torsional buckling resistance** ⑤. The National Annex clarifies that **for all other cases not specifically covered**, the rules given in clause 6.3.2.2 of standard SFS-EN 1993-1-1 should be applied ⑤.

How is execution class typically selected for steel structures?

What determines corrosion allow

Figure 11-4 Example of RAG tool use for document exploration

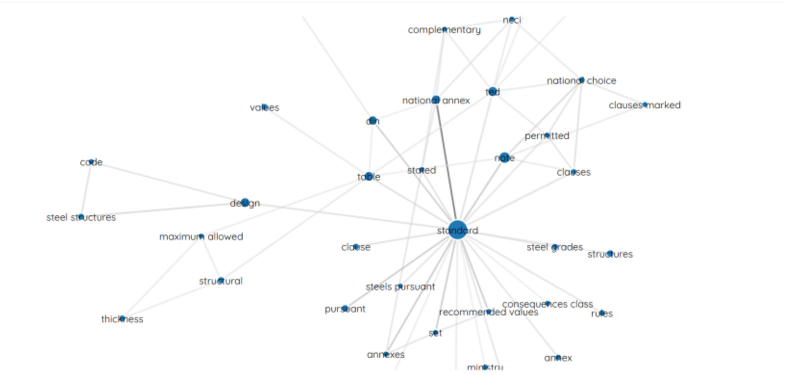


Figure 11-5 Example of knowledge graph use tools to explore information relation

11.2 Implemented example

For the first example case, the computational thinking approach integrated into the statics lectures could be as follows:

1. Problem definition

Objective: Determine the reaction forces, shear force distribution, and bending moment diagram for a simply supported beam with a point load—say, applied at midspan.

Key elements:

- Beam geometry: Define the beam's length and the location of the load.
- Supports: The beam is supported at its ends, with one pin and one roller support.
- Load: A uniform load is applied along the span of the beam.

2. Problem decomposition

Geometry and data input:

- Define the beam length, load magnitude, and load position.
- Discretise the beam into segments (nodes) along its length.

Static equilibrium calculations:

- Compute the reaction forces at the supports using equilibrium conditions (sum of vertical forces and moments).

Shear force calculation:

- For positions before the load, the shear force remains constant.
- For positions after the load, the shear force changes by the magnitude of the load.

Bending moment calculation:

- Integrate the shear force along the beam's length to compute the bending moment at each node.
- Alternatively, use the known analytical expressions for bending moment distribution.

Visualisation:

- Plot the shear force diagram and bending moment diagram using a plotting tool (e.g., Matplotlib).

3. Computational implementation using programming and computational skills

Data structures and input:

Represent the beam as a list or an array of nodes. Define the load and support conditions as parameters. For example, using Python dictionaries or NumPy arrays.

Algorithm Design:

- Input module: Create functions to read or set beam length, load magnitude, and load.

- Equilibrium module: Write a function to compute support reactions using static equilibrium formulas.

Calculation Module:

- Discretise the beam into points.
- Calculate the shear force at each point.
- Integrate (or apply the bending moment formulas) to get the moment values.

Visualisation Module:

- Use Matplotlib to plot the shear force and bending moment diagrams.

Programming tools:

- Python: For programming and for numerical computation.
- NumPy: For efficient array and mathematical operations.
- Matplotlib: For plotting and visualisation of diagrams and charts.

4. Course implementation and integration

Introductory lecture: Introduce the basic principles of beam theory, static equilibrium, and diagram interpretation.

Hands-On Lab:

- Step 1: Have students define the beam's parameters and compute support reactions.
- Step 2: Guide them through discretising the beam and calculating shear forces.
- Step 3: Show how to compute bending moments and plot the diagrams.

Iterative Development:

Start with simple hard-coded values and gradually have students develop functions that accept variable inputs. Encourage them to evaluate their code against known analytical solutions (e.g., the maximum bending moment at the beam’s centre).

Extensions:

Challenge students to modify the code to handle different loading scenarios (like point loads) or to include error checking for unrealistic input parameters.

This approach to a simple engineering problem teaches the student how to decompose structural analysis into smaller tasks, and how to abstract the problem using data structures to design an algorithm to solve equilibrium, shear, and moment computations. Finally, the student can implement the solution using programming tools and languages to reinforce structural and computational thinking skills.[20]

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[20] Other examples are available in the course repository.

12 Conclusion

The available literature provides several conclusions on adopting computational thinking and skills in engineering degrees in the face of the digitalisation of the AEC industry. The limited study conducted for this thesis seems to support those claims and proposes a way forward.

Computational thinking and programming skills are quickly becoming “core competencies” for engineering graduates to effectively engage in digitalisation. As the “fourth industrial revolution” takes place with computer technology at its heart, these skills become crucial for future professional practice. There is a disconnect between discipline knowledge and computational abilities, and to fill this void and increase student motivation, integrating computational skills, including programming, into discipline-specific engineering courses seems a promising approach. Despite the need and potential of discipline-integrated adoption, computational skills face multiple barriers, such as lack of space and time to fit updated content, ingrained perceptions and others; nevertheless, integration of computational skills should not be postponed to avoid further hindering the development of the industry and future engineers’ capabilities.

Computational skills should not focus only on specific technologies but on a problem-solving mindset to better prepare students and future professionals better. This will require an effective integration into the curricula and instructors who possess and can impart computational knowledge from a discipline-specific context. Also, reinforcement and application of a “computational approach” throughout the study years will be essential to prevent students from losing proficiency after introductory courses.

The rate of advancement in technology and digitalisation is exponential. Thus, continuous lifelong learning must be strengthened. Academia and industry need to align to facilitate the digitalisation of the sector. Barriers to adoption and old mentality silos need to be torn down too.

In other words, successfully integrating computational thinking hinges on faculty preparedness and developing effective teaching and assessment methods. The industry must show greater interest in requiring professionals equipped with the skills to adapt to the rapidly evolving digital landscape of the AEC sector.

Addressing the question posed at the beginning of the thesis, is it clear that computational courses have a place in traditional engineering degrees and offer valuable skills and advantages. Thus, postponing their integration harms the students’ professional future and exposes them to rapid sociological and technical advancements. The key components can be learned and integrated with a relevant and contextual approach to the engineering discipline, and if properly executed, initial reticence can be overcome. The question is, will engineering education adapt? Does it have enough time? Is it trying hard enough?

Even further, the fundamental aim of education is to cultivate critically thinking individuals capable of actively engaging in societal discourse and decision-making processes. Engineering education fosters analytical reasoning, problem-solving abilities, and independent judgment, empowering individuals to navigate complexities, identify information, and make informed decisions. A critically thinking society is essential for democracy, innovation, and sustainable development, as it encourages dialogue, questions established norms and promotes continuous improvement. Neglecting education in any form or way undermines societal resilience and progress and leads to worse-off societies.

13 Glossary

PPS as defined in (Eurostat, 2025)

“The purchasing power standard, abbreviated as PPS, is an artificial currency unit. Theoretically, one PPS can buy the same amount of goods and services in each country. However, price differences across borders mean that different amounts of national currency units are needed for the same goods and services depending on the country. PPS are derived by dividing any economic aggregate of a country in national currency by its respective purchasing power parities. PPS is the technical term used by Eurostat for the common currency in which national accounts aggregates are expressed when adjusted for price level differences using PPPs. Thus, PPPs can be interpreted as the exchange rate of the PPS against the euro.”

Industry 4.0 Fourth Industrial Revolution as defined in (European Commission, 2024)

“Industry 4.0 is a term applied to a group of rapid transformations in the design, manufacture, operation and service of manufacturing systems and products. The 4.0 designation signifies that this is the world's fourth industrial revolution, the successor to three earlier industrial revolutions (see Table 1) that caused quantum leaps in productivity and changed the lives of people throughout the world. In the words of German Chancellor Angela Merkel, Industry 4.0 is 'the comprehensive transformation of the whole sphere of industrial production through the merging of digital technology and the internet with conventional industry'.”

Construction 4.0; Industry 4.0 applied to the Construction Industry

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15 Appendix

A1 Survey on Integrating Computational Approaches into Structural Engineering Education (Student survey)

Results shown have been edited to preserve anonymity according to GDPR or for consistency. Anonymised raw survey data may be requested for academic research.

1. Before attending this course, how would you rate your knowledge or exposure to computation and programming?

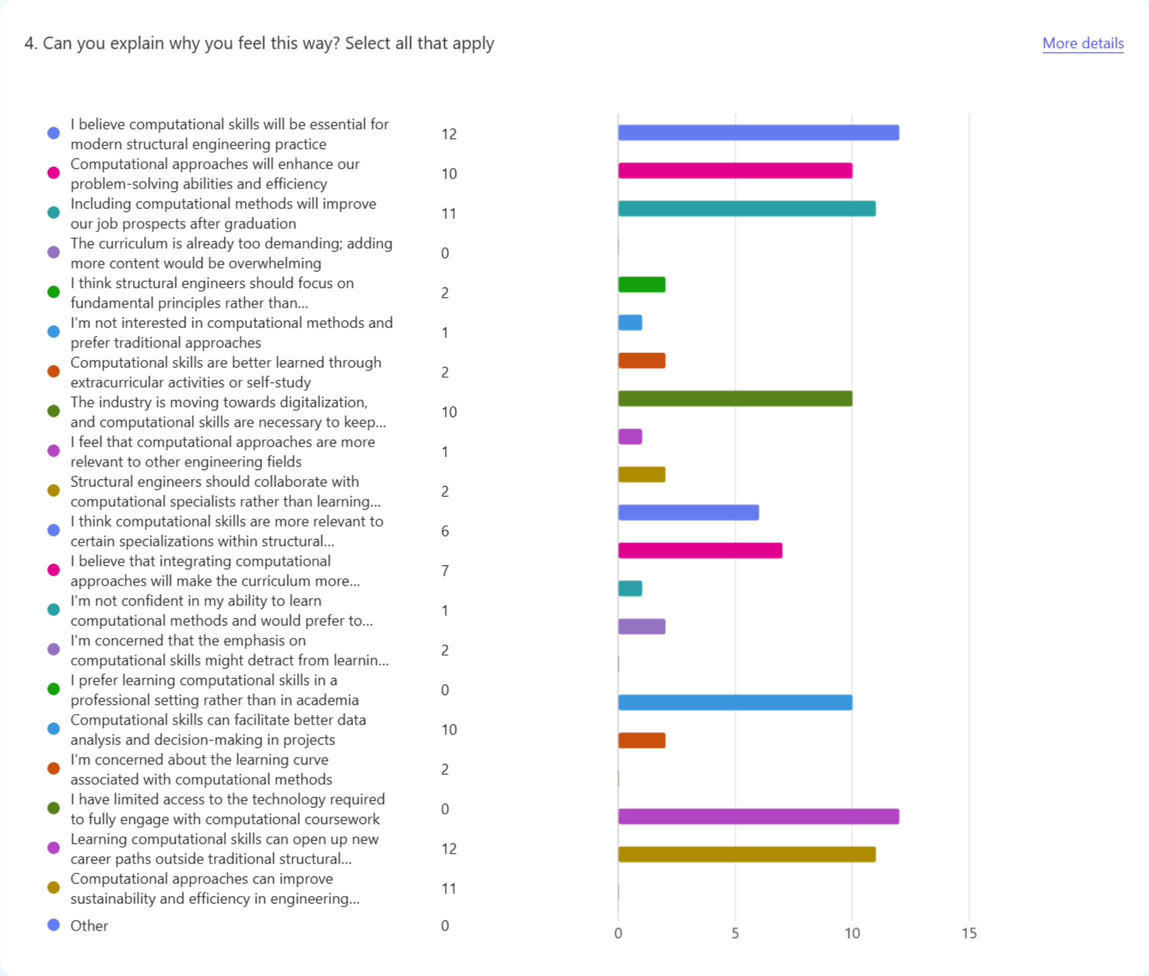
●	I had never engaged with computation or programming before	6
●	I had minimal exposure (e.g., a workshop or a single class)	5
●	I had basic knowledge (e.g., could write simple programs)	3
●	I was moderately experienced (e.g., comfortable with programming tasks)	0
●	I was highly experienced (e.g., extensive programming background)	0

2. After attending this course, how do you personally view the importance of computational skills in your future career as a structural engineer?

●	I believe they will be crucial and will significantly enhance my day-to-day work	3
●	They are important and will help me in several aspects of my job	6
●	They might be important, but I don't see them being part of my daily tasks	4
●	I don't think they will play a significant role in my future career	0
●	I am not sure if they will play a role in my future career	1

3. Should computational approach to structural engineering be part of the structural engineering curriculum?

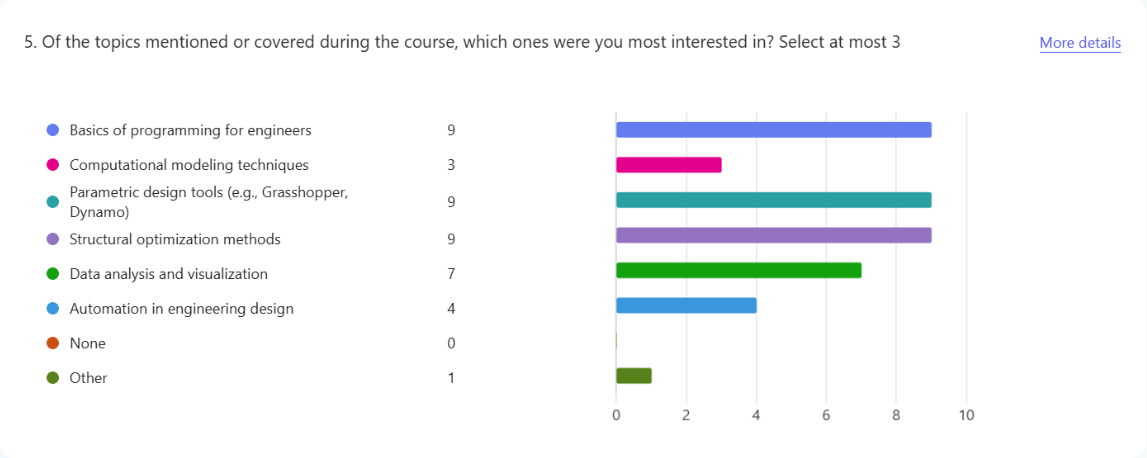
●	Yes, it should be a mandatory part of the curriculum	9
●	Yes, it should be an elective course	4
●	Maybe, it could be an extracurricular workshop	1
●	No, It should not be part of the curriculum	0



4. Can you explain why you feel this way? Select all that apply

More details

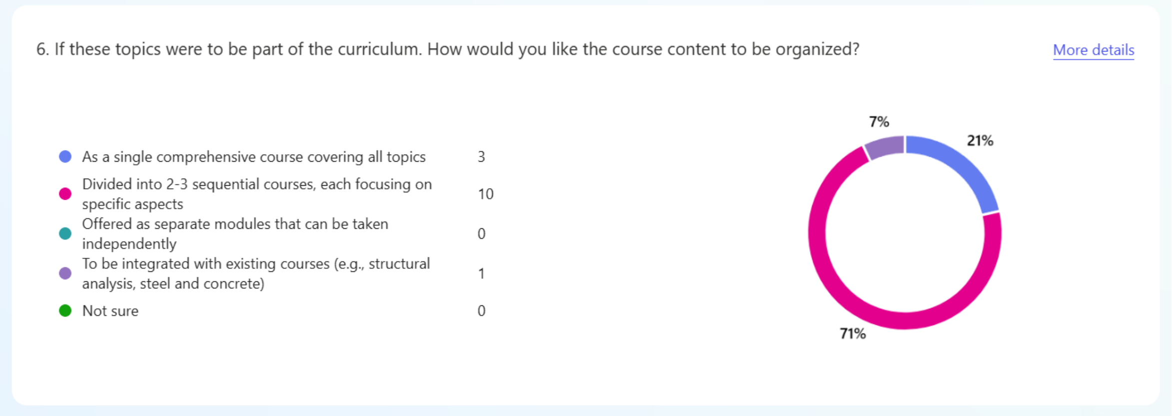
● I believe computational skills will be essential for modern structural engineering practice	12
● Computational approaches will enhance our problem-solving abilities and efficiency	10
● Including computational methods will improve our job prospects after graduation	11
● The curriculum is already too demanding; adding more content would be overwhelming	0
● I think structural engineers should focus on fundamental principles rather than...	2
● I'm not interested in computational methods and prefer traditional approaches	1
● Computational skills are better learned through extracurricular activities or self-study	2
● The industry is moving towards digitalization, and computational skills are necessary to keep...	10
● I feel that computational approaches are more relevant to other engineering fields	1
● Structural engineers should collaborate with computational specialists rather than learning...	2
● I think computational skills are more relevant to certain specializations within structural...	6
● I believe that integrating computational approaches will make the curriculum more...	7
● I'm not confident in my ability to learn computational methods and would prefer to...	1
● I'm concerned that the emphasis on computational skills might detract from learnin...	2
● I prefer learning computational skills in a professional setting rather than in academia	0
● Computational skills can facilitate better data analysis and decision-making in projects	10
● I'm concerned about the learning curve associated with computational methods	2
● I have limited access to the technology required to fully engage with computational coursework	0
● Learning computational skills can open up new career paths outside traditional structural...	12
● Computational approaches can improve sustainability and efficiency in engineering...	11
● Other	0



5. Of the topics mentioned or covered during the course, which ones were you most interested in? Select at most 3

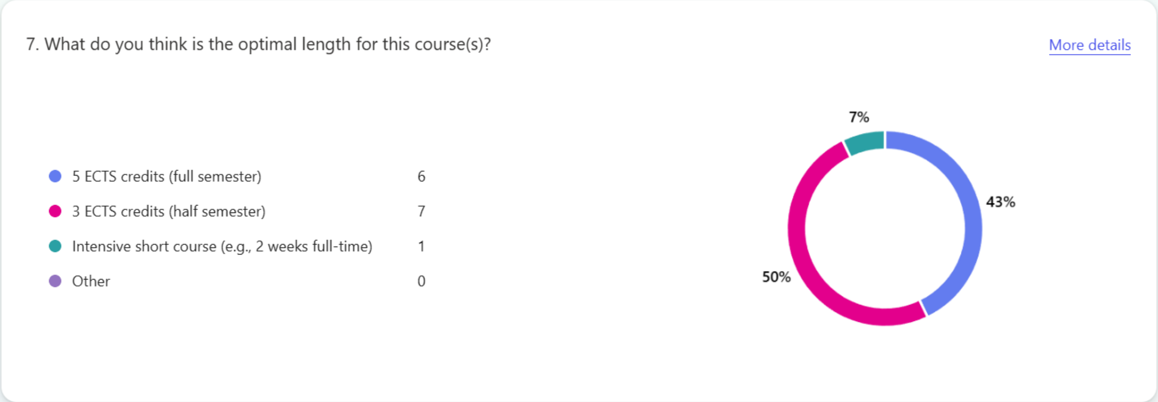
More details

● Basics of programming for engineers	9
● Computational modeling techniques	3
● Parametric design tools (e.g., Grasshopper, Dynamo)	9
● Structural optimization methods	9
● Data analysis and visualization	7
● Automation in engineering design	4
● None	0
● Other	1



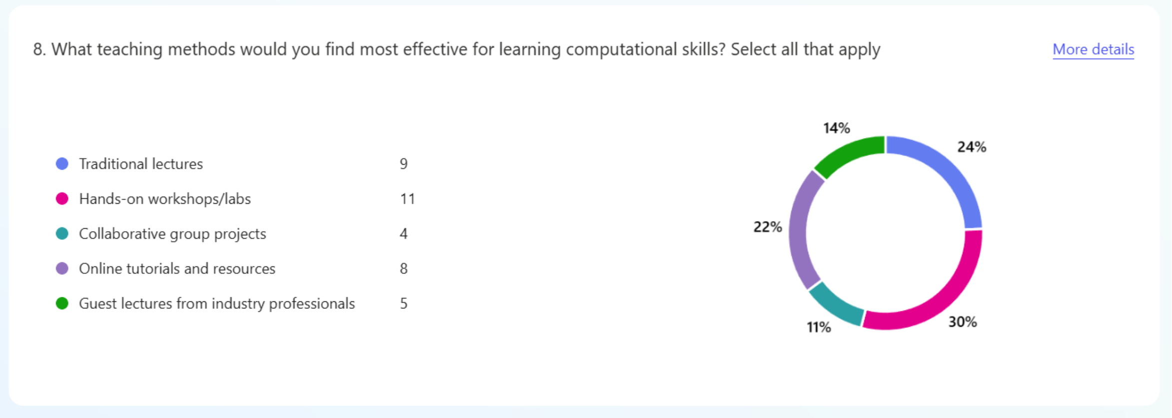
6. If these topics were to be part of the curriculum. How would you like the course content to be organized?

●	As a single comprehensive course covering all topics	3
●	Divided into 2-3 sequential courses, each focusing on specific aspects	10
●	Offered as separate modules that can be taken independently	0
●	To be integrated with existing courses (e.g., structural analysis, steel and concrete)	1
●	Not sure	0



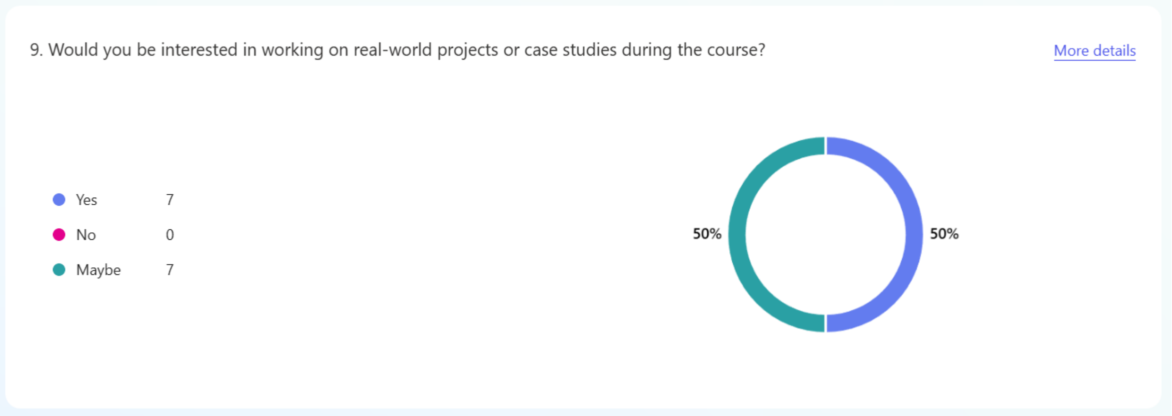
7. What do you think is the optimal length for this course(s)?

●	5 ECTS credits (full semester)	6
●	3 ECTS credits (half semester)	7
●	Intensive short course (e.g., 2 weeks full-time)	1
●	Other	0



8. What teaching methods would you find most effective for learning computational skills? Select all that apply

●	Traditional lectures	9
●	Hands-on workshops/labs	11
●	Collaborative group projects	4
●	Online tutorials and resources	8
●	Guest lectures from industry professionals	5



9. Would you be interested in working on real-world projects or case studies during the course?

●	Yes	7
●	No	0
●	Maybe	7

10. To help you succeed in a computational course, which types of support would you prefer?

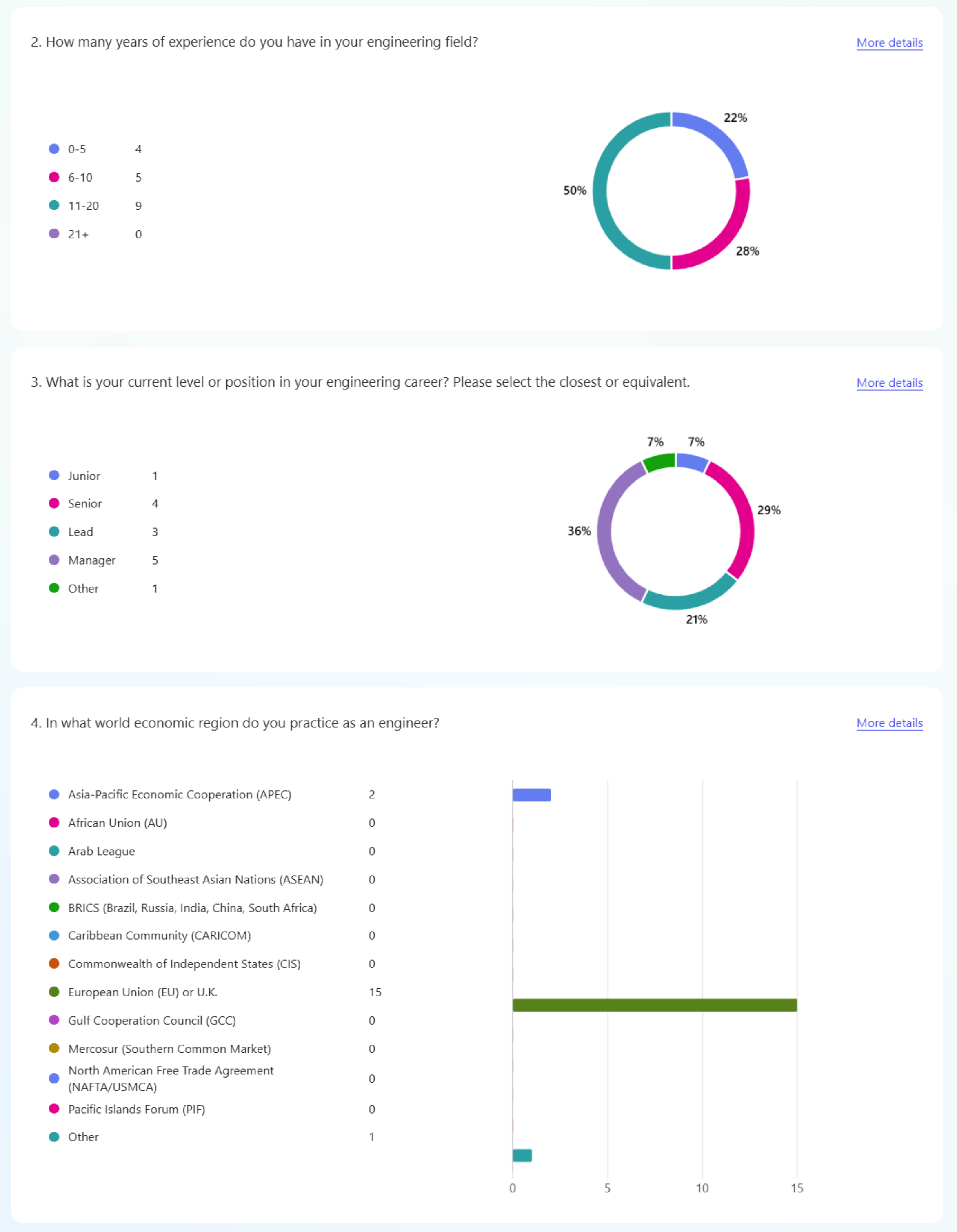
●	Additional mentoring or tutoring opportunities	6
●	Access to a variety of learning materials and online resources	12
●	Participation in collaborative study groups with peers	4
●	Support with software installation and resolving technical problems	3
●	Real-world examples and case studies to illustrate concepts	9
●	Smaller class sizes for more individualized attention	2
●	Accessible course materials for different learning styles (e.g., videos, transcripts)	8
●	Training in foundational computer skills (e.g., typing, file management)	1
●	Integration of computational topics with existing coursework	4
●	Mentorship from senior students or alumni experienced in computational methods	1
●	Workshops on specific software tools or programming languages	5
●	Financial assistance for software licenses or required equipment	3
●	Other	0

A2 Survey on Integrating Computational Approaches into Structural Engineering Education (Professional survey)

Results shown have been edited to preserve anonymity according to GDPR or for consistency. Anonymised raw survey data may be requested for academic research.

1. What is your main engineering field of expertise or current line of work?

● Acoustics Engineering	1
● Airports, Ports & Harbour Engineering	0
● Virtual Digital Construction (VDC) & BIM Engineering	1
● Building Automation Systems Engineering	1
● Bridge & Tunnel Engineering	1
● Civil Engineering	1
● Computational Assisted Engineering & Simulation	0
● Connectivity & Telecommunications Engineering	0
● Construction & Project Management Engineering	1
● Electronics, Embedded Systems & IoT Engineering	0
● Environmental & Sustainability Engineering	0
● Electrical, Electrical systems & Lighting Engineering	0
● Fire Protection & Fire Safety Engineering	0
● Geographical, Geospatial & Remote Sensing Engineering	0
● Geotechnical Engineering	0
● Heat, Power & Energy	0
● HVAC Engineering	0
● Hydraulic Engineering	0
● Industrial Engineering	0
● MEP Engineering	0
● Mechanical Engineering	1
● Material Science & Engineering	0
● Marine & Coastal Engineering	0
● Mining Engineering	0
● Railway Engineering	0
● Resources & Environmental Engineering	0
● Road and Highway Engineering	2
● Smart Infrastructure & Building Systems Engineering	0
● Structural Engineering	6
● Sustainability Engineering	0
● Transport & Traffic Engineering	2
● Urban Infrastructure Engineering	0
● Water, Water resources, Water & Waste Treatment	0
● Waterworks, Waterways, Canal Port Engineering	0
● Other	1



2. How many years of experience do you have in your engineering field?

More details

●	0-5	4
●	6-10	5
●	11-20	9
●	21+	0

3. What is your current level or position in your engineering career? Please select the closest or equivalent.

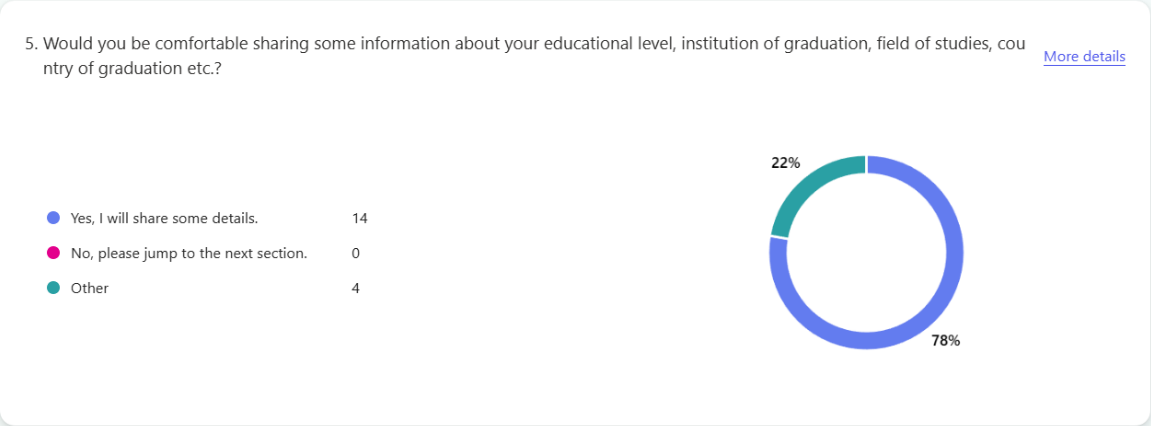
More details

●	Junior	1
●	Senior	4
●	Lead	3
●	Manager	5
●	Other	1

4. In what world economic region do you practice as an engineer?

More details

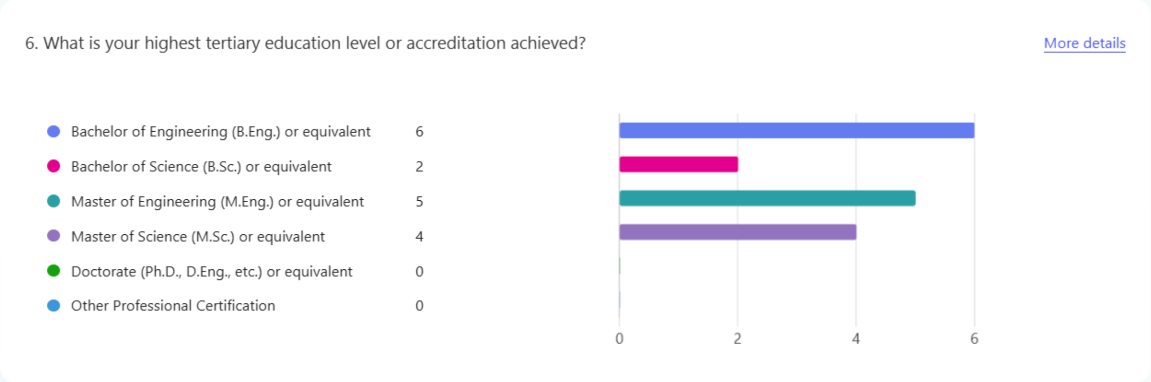
●	Asia-Pacific Economic Cooperation (APEC)	2
●	African Union (AU)	0
●	Arab League	0
●	Association of Southeast Asian Nations (ASEAN)	0
●	BRICS (Brazil, Russia, India, China, South Africa)	0
●	Caribbean Community (CARICOM)	0
●	Commonwealth of Independent States (CIS)	0
●	European Union (EU) or U.K.	15
●	Gulf Cooperation Council (GCC)	0
●	Mercosur (Southern Common Market)	0
●	North American Free Trade Agreement (NAFTA/USMCA)	0
●	Pacific Islands Forum (PIF)	0
●	Other	1



5. Would you be comfortable sharing some information about your educational level, institution of graduation, field of studies, country of graduation etc.?

More details

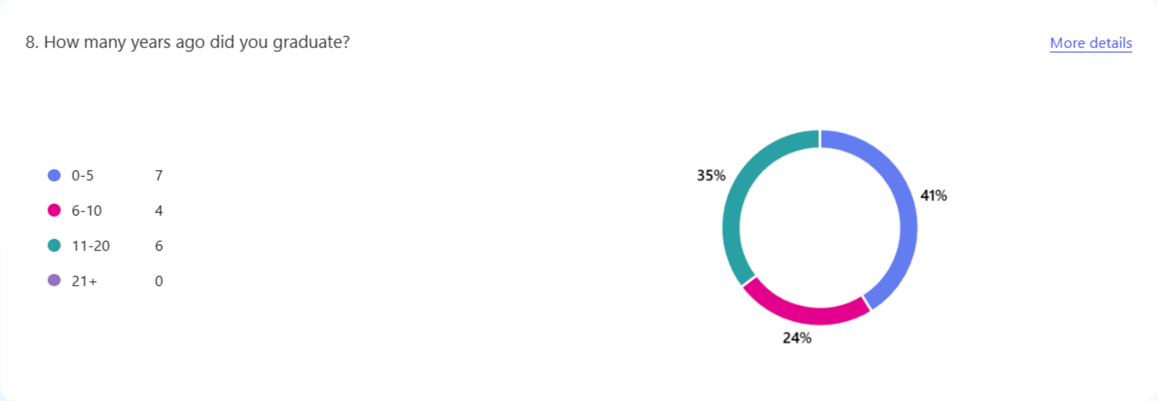
● Yes, I will share some details.	14
● No, please jump to the next section.	0
● Other	4



6. What is your highest tertiary education level or accreditation achieved?

More details

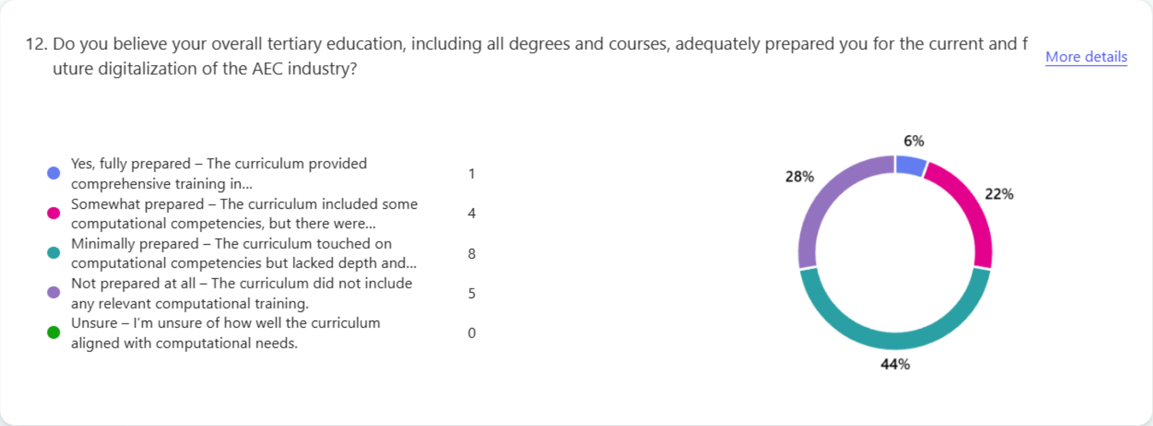
● Bachelor of Engineering (B.Eng.) or equivalent	6
● Bachelor of Science (B.Sc.) or equivalent	2
● Master of Engineering (M.Eng.) or equivalent	5
● Master of Science (M.Sc.) or equivalent	4
● Doctorate (Ph.D., D.Eng., etc.) or equivalent	0
● Other Professional Certification	0



8. How many years ago did you graduate?

More details

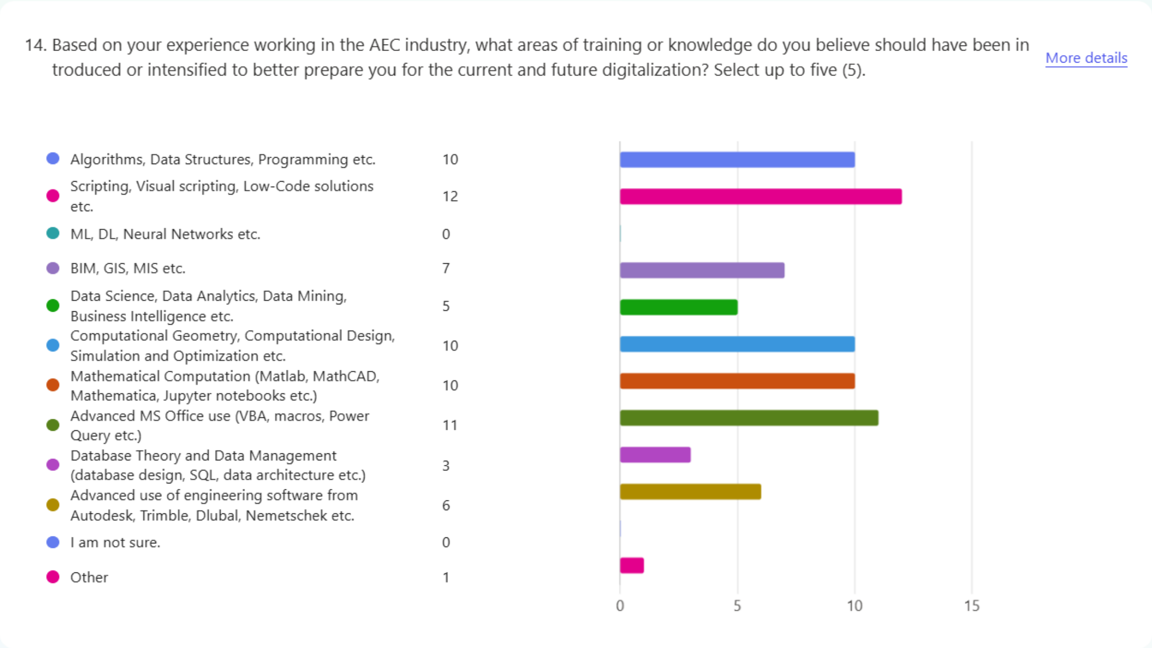
● 0-5	7
● 6-10	4
● 11-20	6
● 21+	0



12. Do you believe your overall tertiary education, including all degrees and courses, adequately prepared you for the current and future digitalization of the AEC industry?

More details

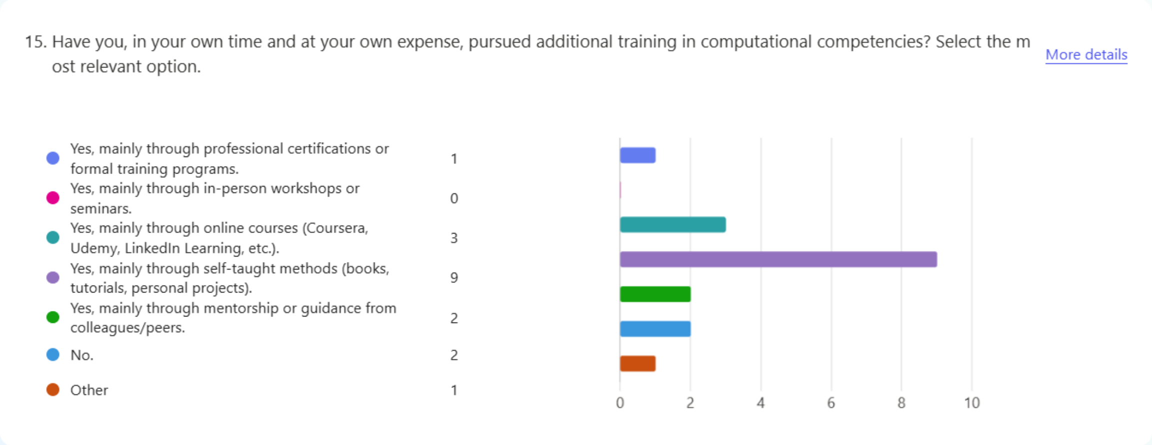
● Yes, fully prepared – The curriculum provided comprehensive training in...	1
● Somewhat prepared – The curriculum included some computational competencies, but there were...	4
● Minimally prepared – The curriculum touched on computational competencies but lacked depth and...	8
● Not prepared at all – The curriculum did not include any relevant computational training.	5
● Unsure – I'm unsure of how well the curriculum aligned with computational needs.	0



14. Based on your experience working in the AEC industry, what areas of training or knowledge do you believe should have been introduced or intensified to better prepare you for the current and future digitalization? Select up to five (5).

More details

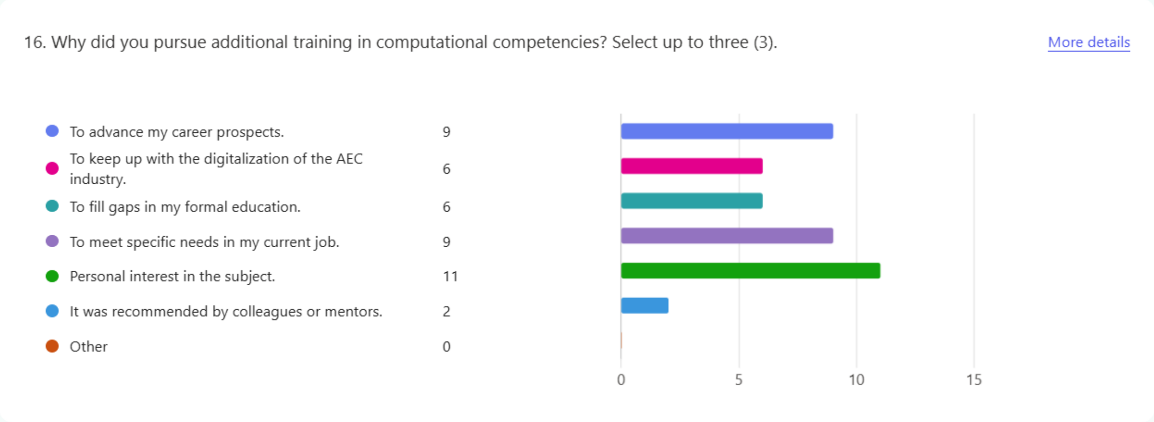
●	Algorithms, Data Structures, Programming etc.	10
●	Scripting, Visual scripting, Low-Code solutions etc.	12
●	ML, DL, Neural Networks etc.	0
●	BIM, GIS, MIS etc.	7
●	Data Science, Data Analytics, Data Mining, Business Intelligence etc.	5
●	Computational Geometry, Computational Design, Simulation and Optimization etc.	10
●	Mathematical Computation (Matlab, MathCAD, Mathematica, Jupyter notebooks etc.)	10
●	Advanced MS Office use (VBA, macros, Power Query etc.)	11
●	Database Theory and Data Management (database design, SQL, data architecture etc.)	3
●	Advanced use of engineering software from Autodesk, Trimble, Dlubal, Nemetschek etc.	6
●	I am not sure.	0
●	Other	1



15. Have you, in your own time and at your own expense, pursued additional training in computational competencies? Select the most relevant option.

More details

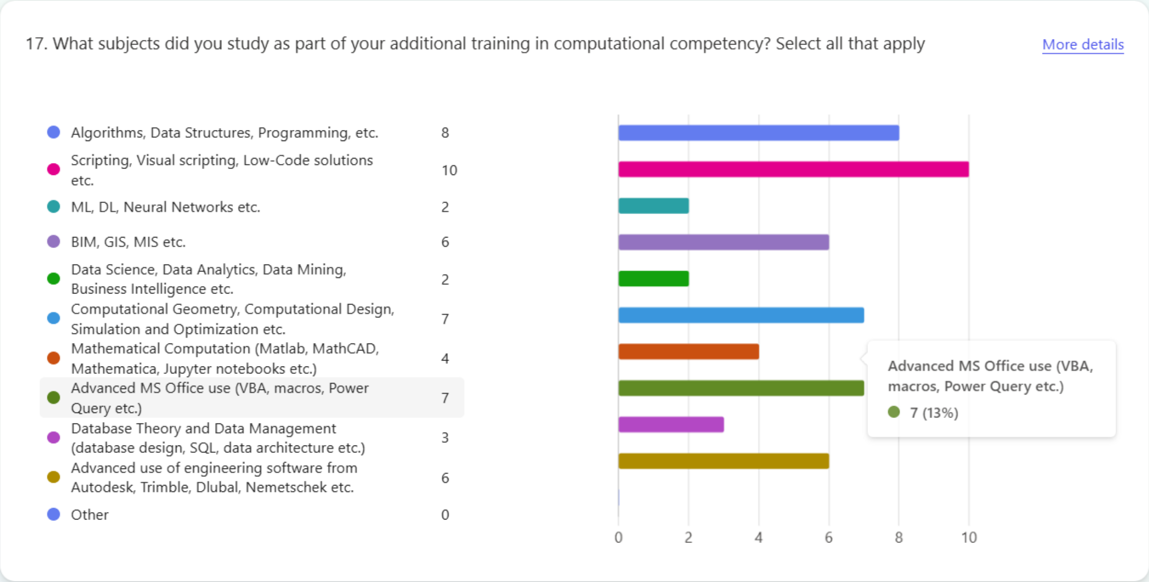
●	Yes, mainly through professional certifications or formal training programs.	1
●	Yes, mainly through in-person workshops or seminars.	0
●	Yes, mainly through online courses (Coursera, Udemy, LinkedIn Learning, etc.).	3
●	Yes, mainly through self-taught methods (books, tutorials, personal projects).	9
●	Yes, mainly through mentorship or guidance from colleagues/peers.	2
●	No.	2
●	Other	1



16. Why did you pursue additional training in computational competencies? Select up to three (3).

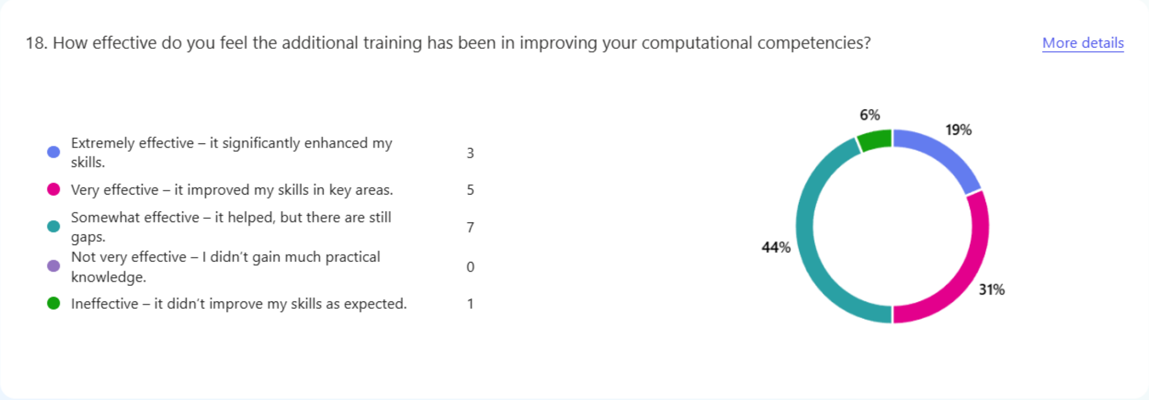
More details

●	To advance my career prospects.	9
●	To keep up with the digitalization of the AEC industry.	6
●	To fill gaps in my formal education.	6
●	To meet specific needs in my current job.	9
●	Personal interest in the subject.	11
●	It was recommended by colleagues or mentors.	2
●	Other	0



17. What subjects did you study as part of your additional training in computational competency? Select all that apply

Algorithms, Data Structures, Programming, etc.	8
Scripting, Visual scripting, Low-Code solutions etc.	10
ML, DL, Neural Networks etc.	2
BIM, GIS, MIS etc.	6
Data Science, Data Analytics, Data Mining, Business Intelligence etc.	2
Computational Geometry, Computational Design, Simulation and Optimization etc.	7
Mathematical Computation (Matlab, MathCAD, Mathematica, Jupyter notebooks etc.)	4
Advanced MS Office use (VBA, macros, Power Query etc.)	7
Database Theory and Data Management (database design, SQL, data architecture etc.)	3
Advanced use of engineering software from Autodesk, Trimble, Dlubal, Nemetschek etc.	6
Other	0



18. How effective do you feel the additional training has been in improving your computational competencies?

Extremely effective – it significantly enhanced my skills.	3
Very effective – it improved my skills in key areas.	5
Somewhat effective – it helped, but there are still gaps.	7
Not very effective – I didn't gain much practical knowledge.	0
Ineffective – it didn't improve my skills as expected.	1

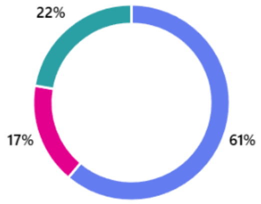
19. If you have not pursued additional training in computational competencies, what are the three main reasons that have stopped you? Select up to five (5).

Lack of time.	0
Cost of training.	0
I didn't see the need for it.	1
Difficulty finding relevant training.	0
No support from my employer.	0
Uncertainty about which skills to focus on.	1
I prefer learning on the job.	1
Lack of confidence in completing the training.	0
Computational competencies will never be relevant to my role.	0
I plan to pursue training but haven't yet.	0
Concern that the training wasn't "official" or accredited enough.	0
Other	0

20. Are you comfortable sharing some details about any computational competency training provided by your employer?

More details

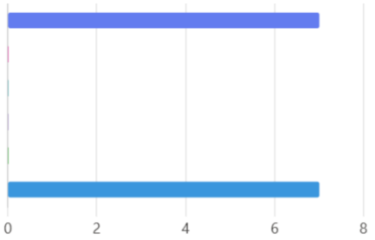
● Yes, I will share some details.	11
● No, please jump to the next section.	3
● Other	4



21. Have you received any additional computational competency training paid for or provided by your employer?

More details

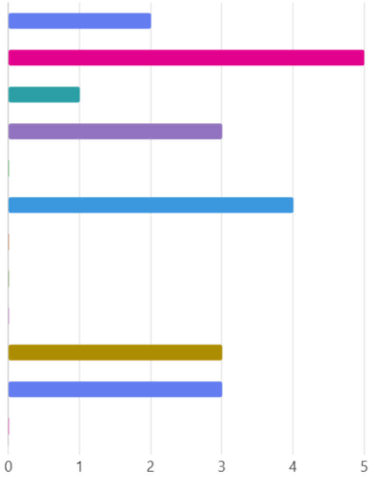
● Yes, during paid work hours.	7
● Yes, outside of work hours but remunerated by the employer.	0
● Yes, outside of work hours and not remunerated, but the course was paid for by the employer.	0
● Yes, through online courses (Udemy, Coursera, etc.) paid by the employer, during paid work...	0
● Yes, through online courses (Udemy, Coursera, etc.) paid by the employer, but outside of work...	0
● No, I have not received any employer-provided training.	7

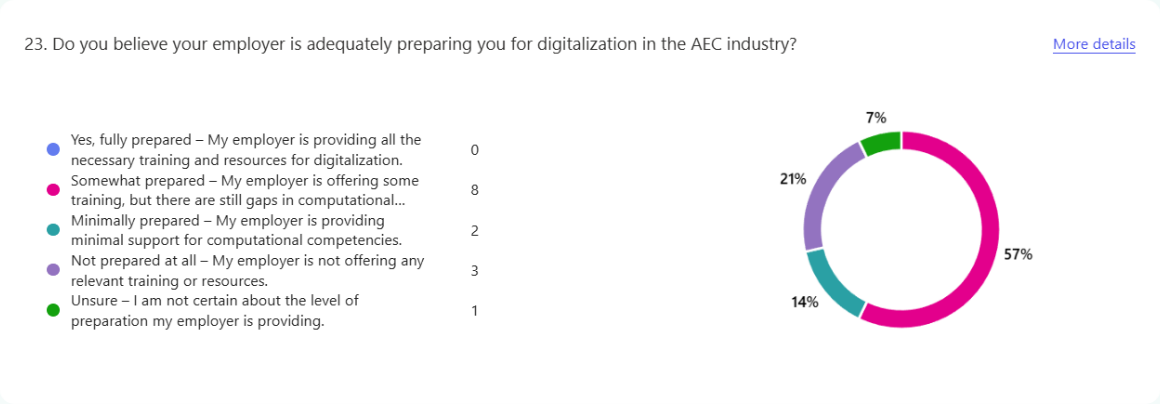


22. Which areas of computational competency were covered in the courses provided by your employer? Select all that apply.

More details

● Algorithms, Data Structures, Programming etc.	2
● Scripting, Visual scripting, Low-Code solutions etc.	5
● ML, DL, Neural Networks etc.	1
● BIM, GIS, MIS etc.	3
● Data Science, Data Analytics, Data Mining, Business Intelligence etc.	0
● Computational Geometry, Computational design, Simulation and Optimization etc.	4
● Mathematical Computation (Matlab, MathCAD, Mathematica, Jupyter notebooks).	0
● Advanced MS Office use (VBA, macros, Power Query)	0
● Database Theory and Data Management (database design, SQL, data architecture etc.)	0
● Advanced use of engineering software from Autodesk, Trimble, Dlubal, Nemetschek etc.	3
● I am not sure.	3
● Other	0

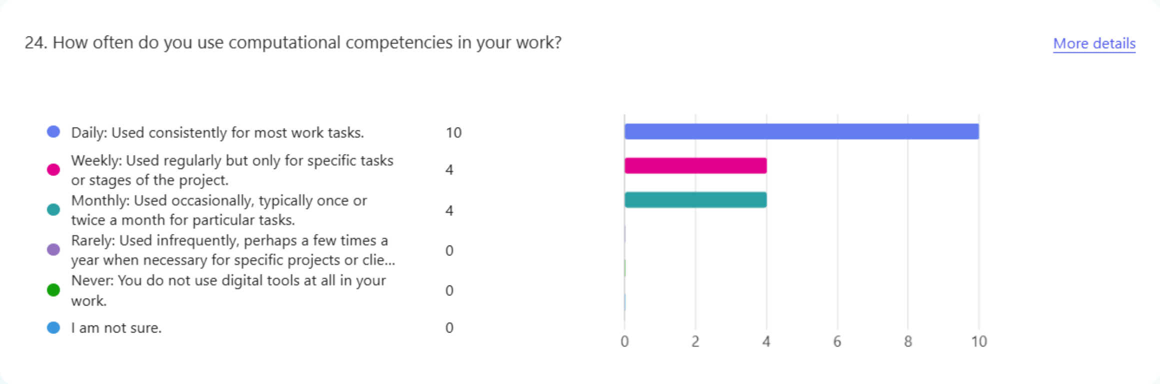




23. Do you believe your employer is adequately preparing you for digitalization in the AEC industry?

More details

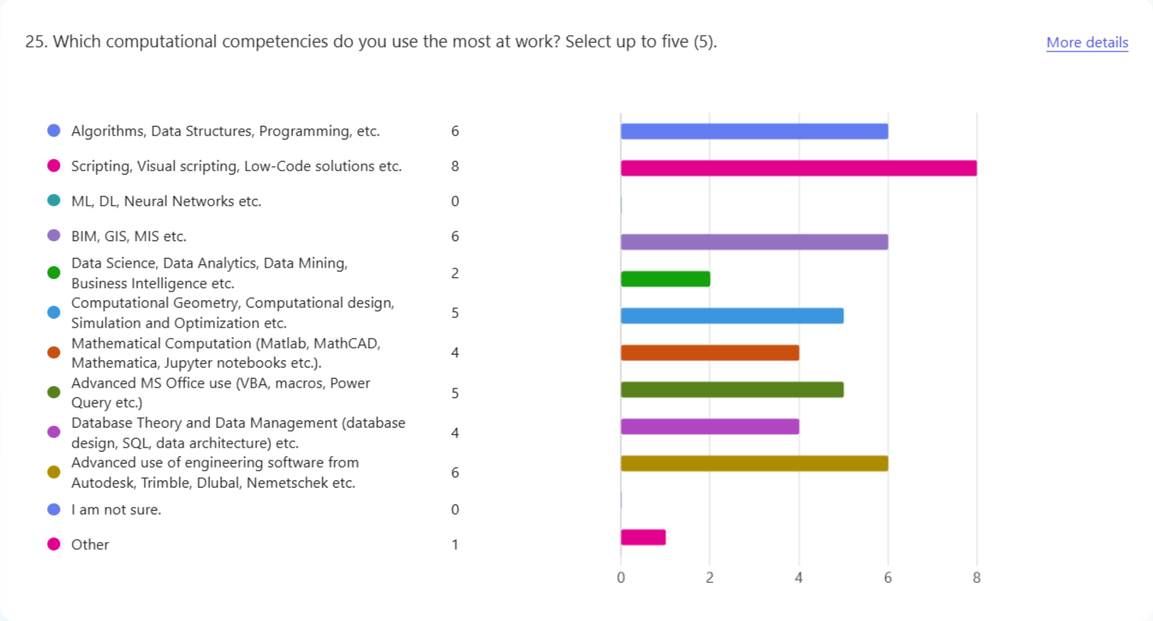
●	Yes, fully prepared – My employer is providing all the necessary training and resources for digitalization.	0
●	Somewhat prepared – My employer is offering some training, but there are still gaps in computational...	8
●	Minimally prepared – My employer is providing minimal support for computational competencies.	2
●	Not prepared at all – My employer is not offering any relevant training or resources.	3
●	Unsure – I am not certain about the level of preparation my employer is providing.	1



24. How often do you use computational competencies in your work?

More details

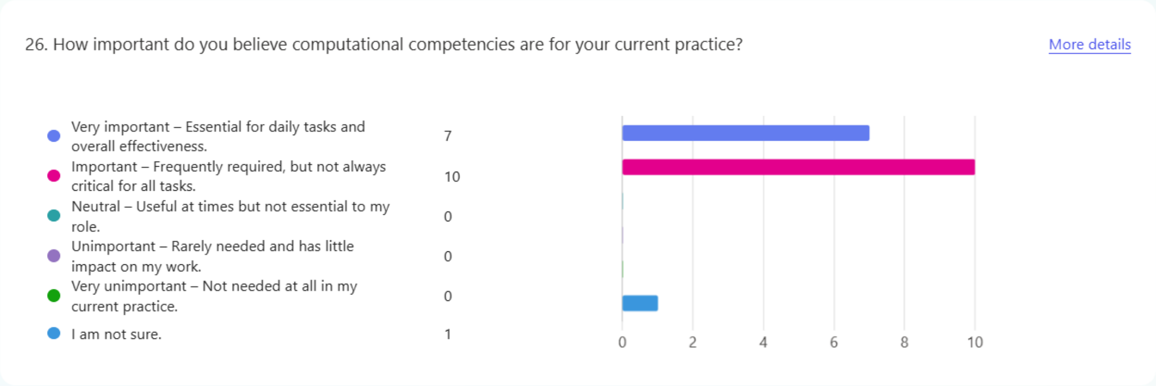
●	Daily: Used consistently for most work tasks.	10
●	Weekly: Used regularly but only for specific tasks or stages of the project.	4
●	Monthly: Used occasionally, typically once or twice a month for particular tasks.	4
●	Rarely: Used infrequently, perhaps a few times a year when necessary for specific projects or clie...	0
●	Never: You do not use digital tools at all in your work.	0
●	I am not sure.	0



25. Which computational competencies do you use the most at work? Select up to five (5).

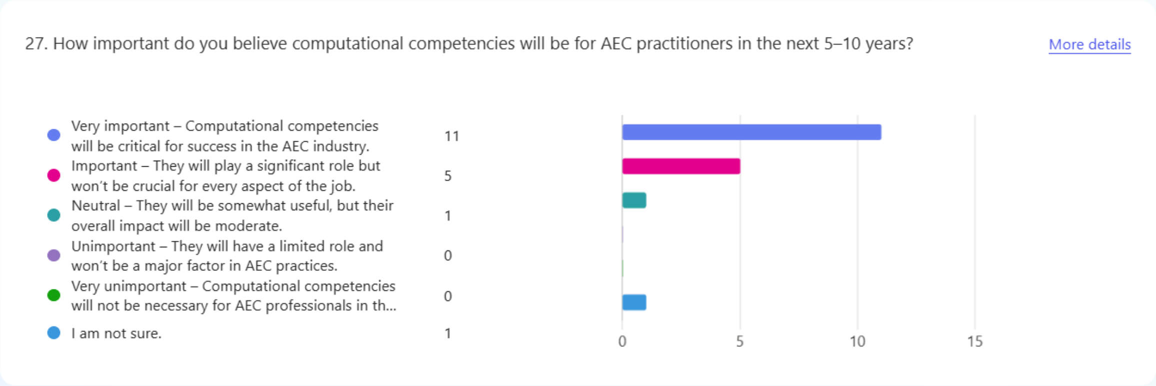
More details

●	Algorithms, Data Structures, Programming, etc.	6
●	Scripting, Visual scripting, Low-Code solutions etc.	8
●	ML, DL, Neural Networks etc.	0
●	BIM, GIS, MIS etc.	6
●	Data Science, Data Analytics, Data Mining, Business Intelligence etc.	2
●	Computational Geometry, Computational design, Simulation and Optimization etc.	5
●	Mathematical Computation (Matlab, MathCAD, Mathematica, Jupyter notebooks etc.).	4
●	Advanced MS Office use (VBA, macros, Power Query etc.)	5
●	Database Theory and Data Management (database design, SQL, data architecture) etc.	4
●	Advanced use of engineering software from Autodesk, Trimble, Dlubal, Nemetschek etc.	6
●	I am not sure.	0
●	Other	1



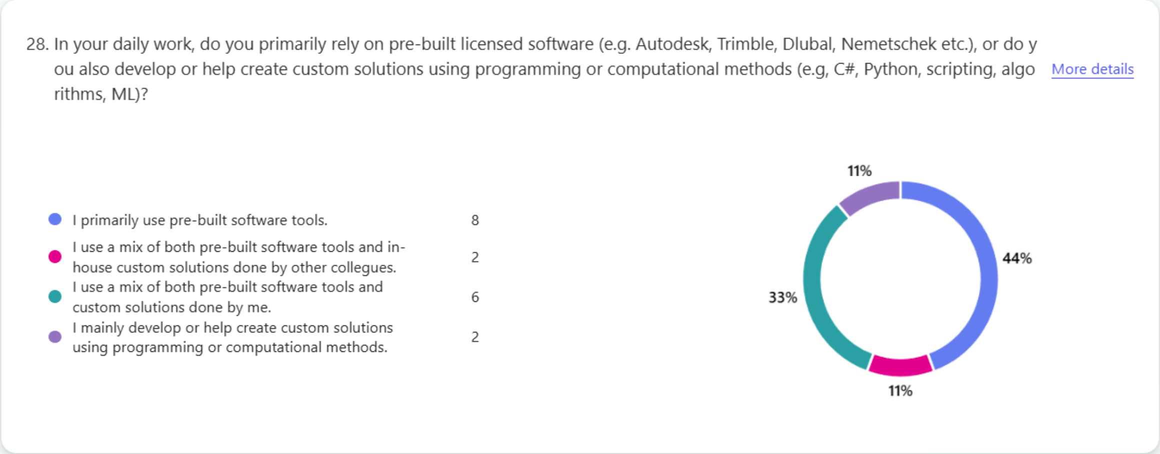
26. How important do you believe computational competencies are for your current practice?

Very important – Essential for daily tasks and overall effectiveness.	7
Important – Frequently required, but not always critical for all tasks.	10
Neutral – Useful at times but not essential to my role.	0
Unimportant – Rarely needed and has little impact on my work.	0
Very unimportant – Not needed at all in my current practice.	0
I am not sure.	1



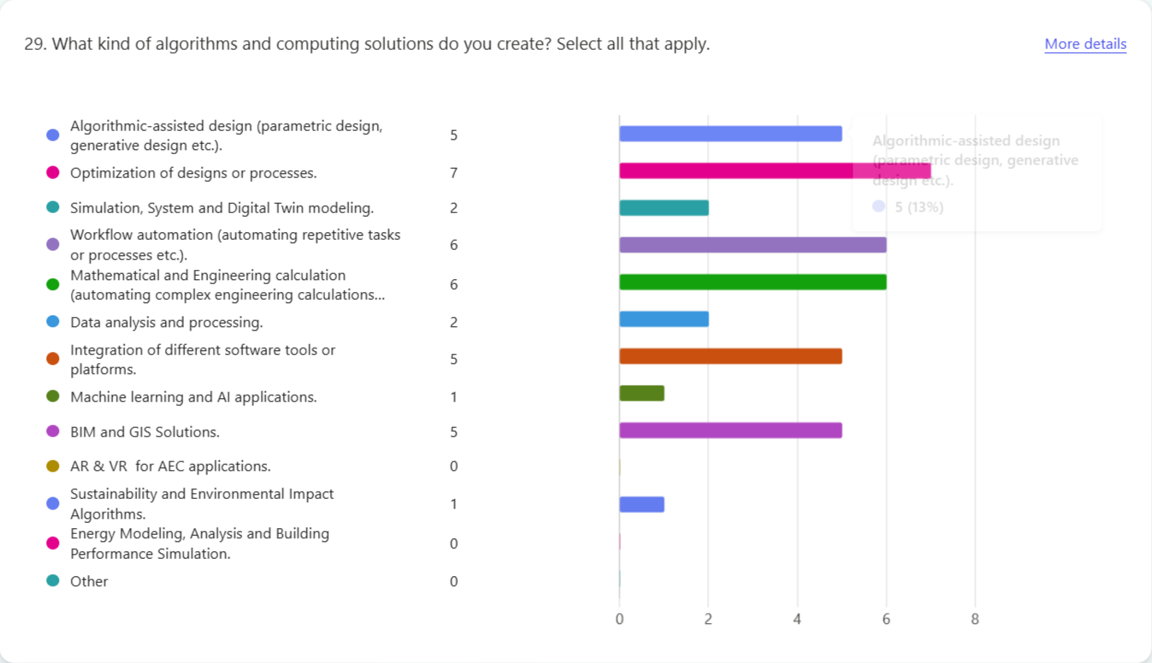
27. How important do you believe computational competencies will be for AEC practitioners in the next 5–10 years?

Very important – Computational competencies will be critical for success in the AEC industry.	11
Important – They will play a significant role but won't be crucial for every aspect of the job.	5
Neutral – They will be somewhat useful, but their overall impact will be moderate.	1
Unimportant – They will have a limited role and won't be a major factor in AEC practices.	0
Very unimportant – Computational competencies will not be necessary for AEC professionals in th...	0
I am not sure.	1



28. In your daily work, do you primarily rely on pre-built licensed software (e.g. Autodesk, Trimble, Dlubal, Nemetschek etc.), or do you also develop or help create custom solutions using programming or computational methods (e.g, C#, Python, scripting, algorithms, ML)?

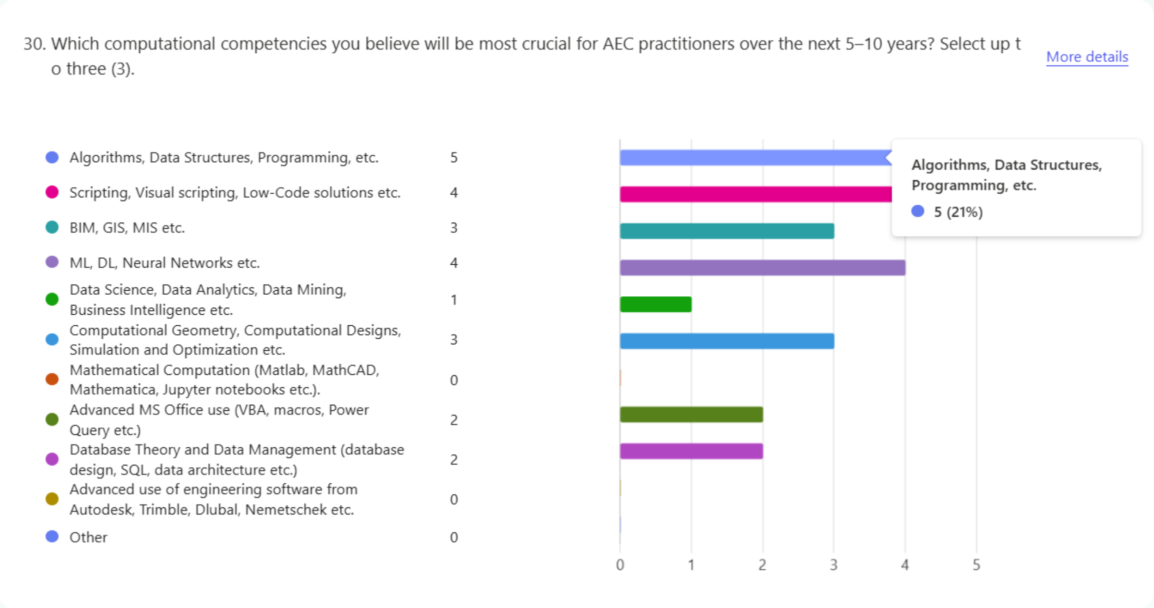
I primarily use pre-built software tools.	8
I use a mix of both pre-built software tools and in-house custom solutions done by other collegues.	2
I use a mix of both pre-built software tools and custom solutions done by me.	6
I mainly develop or help create custom solutions using programming or computational methods.	2



29. What kind of algorithms and computing solutions do you create? Select all that apply.

● Algorithmic-assisted design (parametric design, generative design etc.).	5
● Optimization of designs or processes.	7
● Simulation, System and Digital Twin modeling.	2
● Workflow automation (automating repetitive tasks or processes etc.).	6
● Mathematical and Engineering calculation (automating complex engineering calculations...	6
● Data analysis and processing.	2
● Integration of different software tools or platforms.	5
● Machine learning and AI applications.	1
● BIM and GIS Solutions.	5
● AR & VR for AEC applications.	0
● Sustainability and Environmental Impact Algorithms.	1
● Energy Modeling, Analysis and Building Performance Simulation.	0
● Other	0

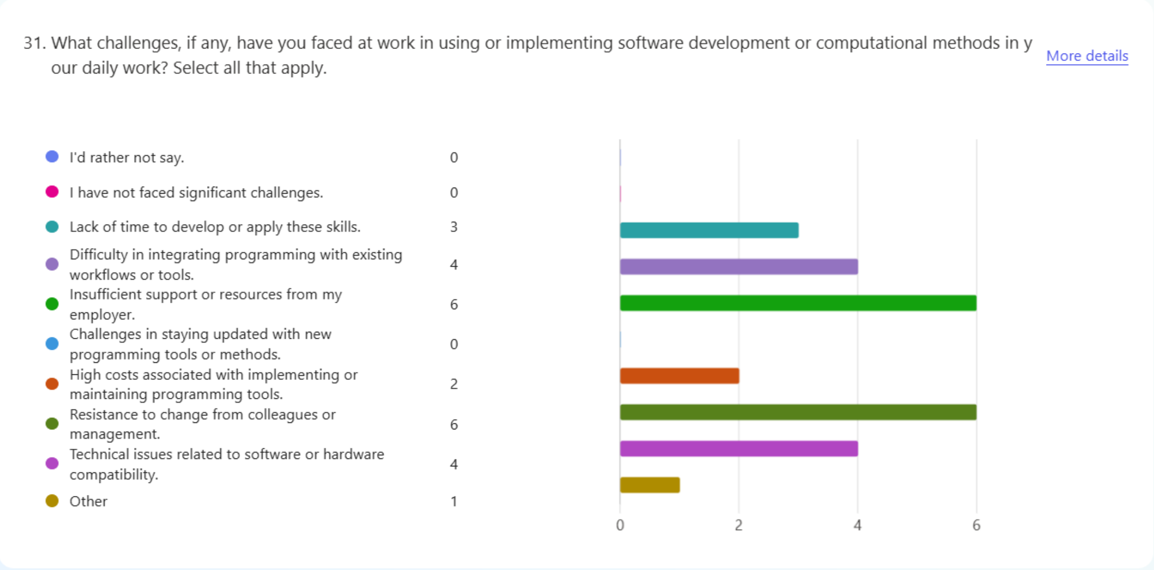
Algorithmic-assisted design (parametric design, generative design etc.).
● 5 (13%)



30. Which computational competencies you believe will be most crucial for AEC practitioners over the next 5–10 years? Select up to three (3).

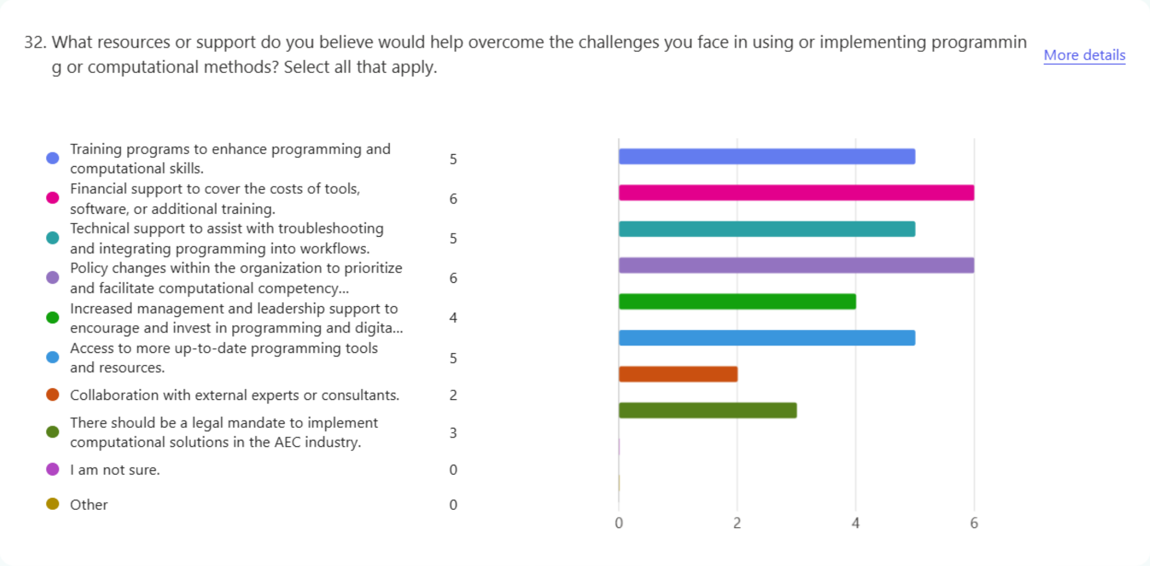
● Algorithms, Data Structures, Programming, etc.	5
● Scripting, Visual scripting, Low-Code solutions etc.	4
● BIM, GIS, MIS etc.	3
● ML, DL, Neural Networks etc.	4
● Data Science, Data Analytics, Data Mining, Business Intelligence etc.	1
● Computational Geometry, Computational Designs, Simulation and Optimization etc.	3
● Mathematical Computation (Matlab, MathCAD, Mathematica, Jupyter notebooks etc.).	0
● Advanced MS Office use (VBA, macros, Power Query etc.)	2
● Database Theory and Data Management (database design, SQL, data architecture etc.)	2
● Advanced use of engineering software from Autodesk, Trimble, Dlubal, Nemetschek etc.	0
● Other	0

Algorithms, Data Structures, Programming, etc.
● 5 (21%)



31. What challenges, if any, have you faced at work in using or implementing software development or computational methods in your daily work? Select all that apply.

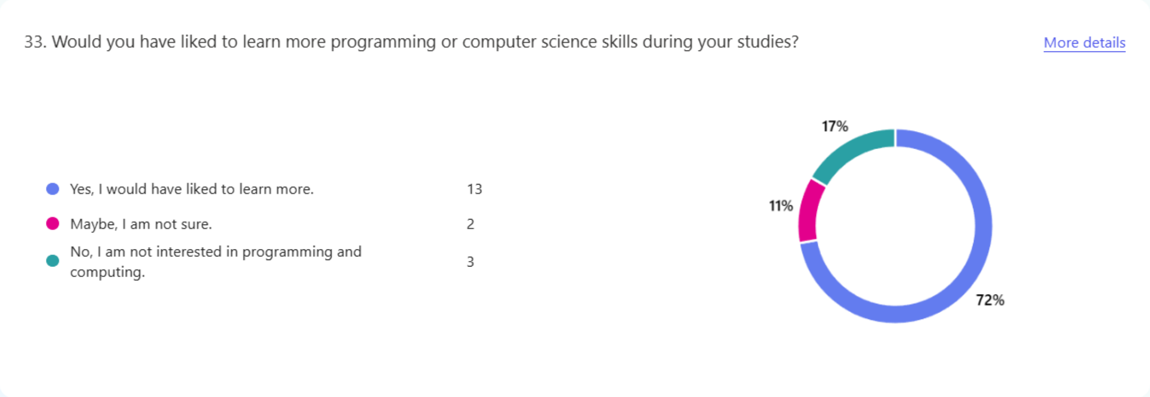
● I'd rather not say.	0
● I have not faced significant challenges.	0
● Lack of time to develop or apply these skills.	3
● Difficulty in integrating programming with existing workflows or tools.	4
● Insufficient support or resources from my employer.	6
● Challenges in staying updated with new programming tools or methods.	0
● High costs associated with implementing or maintaining programming tools.	2
● Resistance to change from colleagues or management.	6
● Technical issues related to software or hardware compatibility.	4
● Other	1



32. What resources or support do you believe would help overcome the challenges you face in using or implementing programming or computational methods? Select all that apply.

More details

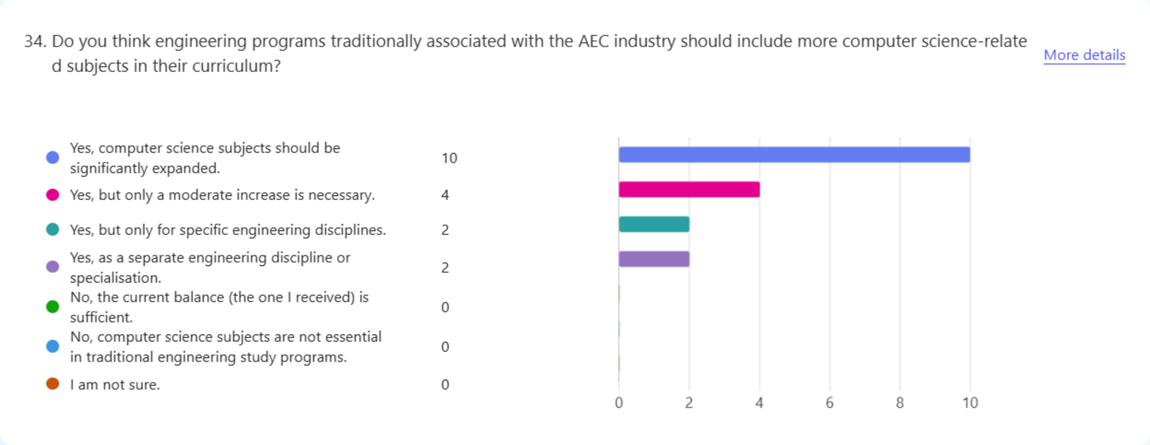
●	Training programs to enhance programming and computational skills.	5
●	Financial support to cover the costs of tools, software, or additional training.	6
●	Technical support to assist with troubleshooting and integrating programming into workflows.	5
●	Policy changes within the organization to prioritize and facilitate computational competency...	6
●	Increased management and leadership support to encourage and invest in programming and digita...	4
●	Access to more up-to-date programming tools and resources.	5
●	Collaboration with external experts or consultants.	2
●	There should be a legal mandate to implement computational solutions in the AEC industry.	3
●	I am not sure.	0
●	Other	0



33. Would you have liked to learn more programming or computer science skills during your studies?

More details

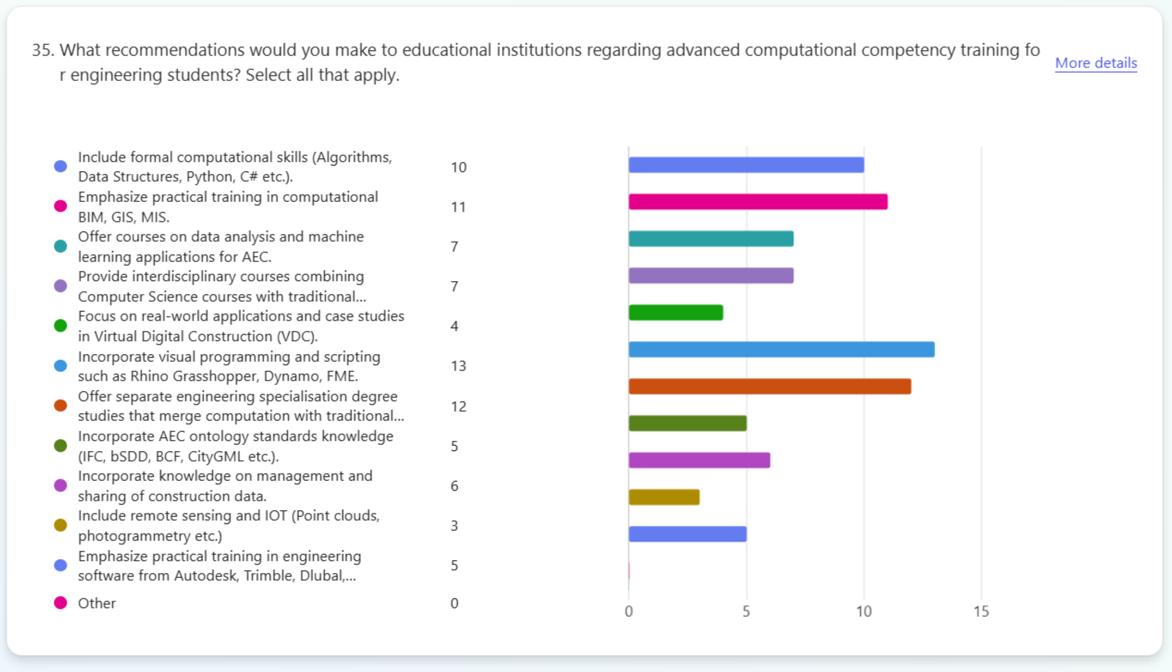
●	Yes, I would have liked to learn more.	13
●	Maybe, I am not sure.	2
●	No, I am not interested in programming and computing.	3



34. Do you think engineering programs traditionally associated with the AEC industry should include more computer science-related subjects in their curriculum?

More details

●	Yes, computer science subjects should be significantly expanded.	10
●	Yes, but only a moderate increase is necessary.	4
●	Yes, but only for specific engineering disciplines.	2
●	Yes, as a separate engineering discipline or specialisation.	2
●	No, the current balance (the one I received) is sufficient.	0
●	No, computer science subjects are not essential in traditional engineering study programs.	0
●	I am not sure.	0



35. What recommendations would you make to educational institutions regarding advanced computational competency training for engineering students? Select all that apply.

Include formal computational skills (Algorithms, Data Structures, Python, C# etc.).	10
Emphasize practical training in computational BIM, GIS, MIS.	11
Offer courses on data analysis and machine learning applications for AEC.	7
Provide interdisciplinary courses combining Computer Science courses with traditional...	7
Focus on real-world applications and case studies in Virtual Digital Construction (VDC).	4
Incorporate visual programming and scripting such as Rhino Grasshopper, Dynamo, FME.	13
Offer separate engineering specialisation degree studies that merge computation with traditional...	12
Incorporate AEC ontology standards knowledge (IFC, bSDD, BCF, CityGML etc.).	5
Incorporate knowledge on management and sharing of construction data.	6
Include remote sensing and IOT (Point clouds, photogrammetry etc.)	3
Emphasize practical training in engineering software from Autodesk, Trimble, Dlubal,...	5
Other	0