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A ‘snapshot’ of engineering practitioners views of ChatGPT-informing pedagogy in higher education

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ABSTRACT

A new discourse has proliferated in teaching and learning committee meetings- Large Language Models (LLMs), most commonly Chat Generative Pre-Trained Transformer (ChatGPT). ChatGPT ‘went viral’ across HEIs during 2022 and it could be said that for academics, this has been more ‘shock’ than ‘awe’. A shock that this Artificial Intelligence (AI) software can generate semi-credible coursework, and that students have swiftly enacted their agency. In this paper we take an ‘employability’ lens on ChatGPT and contribute to a growing body of research on AI within HEIs. Through understanding how employers and their employees are adopting LLMs in their workplace. Our Qualtrics survey of practicing engineers (N = 86) was undertaken over a four-week period during the period June-July 2023 and provides a ‘snapshot’ in time. That is, given the rapidity of how ChatGPT is metamorphosing, our data and subsequent conclusions are attributable to a version ChatGPT 3-3.5 in use during this period.

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Introduction

> We are going through tremendous changes in our times, so much so that it is thrilling, exhilarating, and exciting, as well as perhaps scary (Broo, Kaynak, and Sait 2022, 6).

Anecdotal evidence would suggest that the narrative above reflects the experience of engineering academics in Higher Education Institutions (HEIs) who are experiencing a rapid and transformational change associated with the introduction and of Large Language Models (LLMs) such as Chat Generative Pre-Trained Transformer (ChatGPT). A cursory glance at headlines in the Times Higher Education (THE) publication suggests that, more than ever before, there is no place for luddites within HEIs:

- AI in higher education: dystopia, utopia or something in between?
- ChatGPT as a teaching tool, not a cheating tool.
- How can generative AI intersect with Bloom’s taxonomy?

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- AI pioneer: ChatGPT will soon become scholars' debate partner.
- Three ways to use ChatGPT to enhance students' critical thinking in the classroom.

In this paper we take the position that engineering programmes should provide students with an authentic curriculum that reflects real industry practice. Over the years our engineering students have used technology (i.e. slide rules, calculators, Computer Aided Design software) to prepare them for work. Indeed, Bell (2025) found that engineers in Australia named these technologies and were concerned about losing traditional skills through the adoption of GenAI. Nonetheless, contemporary Artificial Intelligence (AI) related job adverts are seeking employees with experience of LLMs, particularly prompt engineering skills (Kutela et al. 2023). It can be expected that graduate engineering job adverts will feature this requirement soon. ChatGPT provides engineering educators with an opportunity to break free from the disciplines focus on closed book exams, with the ubiquitous tightly bounded correct answer problems (Francis and Norton 2024; Lucas, Hanson, and Claxton 2014), away from a teaching-centered 'banking model' pedagogy. ChatGPT provides a catalyst to impart our students with agency, to pique their curiosity, to help them question, reflect and think like engineers, and to prepare them for workplaces that will require the use of GenAI tools. Given that 'the ChatGPT research field is still in its infancy' (Gao et al. 2024, 18) our research is tentative and exploratory, as such, our research question is – *What exposure have engineers in industry had to ChatGPT and how can this knowledge help us to inform our engineering programmes?*

In the following section of the paper, we examine AI, specifically LLMs in the context of a new technology within HEIs. The next section critiques how AI can provide academics with an opportunity to reconsider their pedagogy. We then focus on engineering education and provide a justification for practicing engineers advisory role in our programmes. The methodology, results and discussion sections are then presented, followed by our conclusion and recommendations for future studies.

Technology, Artificial Intelligence and Large Language Models (LLMs)

> Every now and again some innovation necessitates radical change and re-thinking of how things need to be done in the future (Heywood 2012, 3)

Our students' personal and educational adaptation of technology appears contradictory. They can display luddite behaviour in their home lives by popularising Polaroids (Klara 2020) or by driving up the sales of vinyl records (Jones 2021), whilst at university they have used ChatGPT to complete university work (Hennessey 2023). If our students are displaying 'fickle' behaviour in relation to technology, then it would be pertinent to ensure we provide an authentic curriculum that reflects how engineers in industry are adapting to AI and specifically to LLMs such as ChatGPT. That said 'we can't yet know what kinds of cheating ChatGPT might make possible in the future. We can't yet know if we have a full taxonomy of ChatGPT-enhanced mischief' (Muir 2023).

Freeman (2024, 14) notes that 'generative AI has quickly become normalised among students in higher education'. By 2025 he concluded that 'the time of widespread use of generative AI in higher education is not just inevitable but has already arrived' (Freeman 2025, 11). ChatGPT has 'gone viral', the genie cannot be put back into the bottle. Indeed, in an academic experience survey of over 10,000 undergraduate students in the UK (Neves et al. 2024, 8) the authors found that 'one in three students use artificial intelligence (AI) to help with their studies at least once a week'. However, O'Dea (2024, 4) notes that 'it is still too early to say whether GenAI is or will be the paradigm shift for higher education'. However (Cengage 2024, 5) posit that GenAI has the potential to reshape 'the very nature of teaching and learning in the years to come'.

HEIs have begun to adapt and develop policy and practice for ChatGPT (Scottish Government 2023) and academics have sought reassurance and guidance from their institutions, regulatory bodies, and from the European Society for Engineering Education (SEFI) community of practice

(Johri, Lindsay, and Qadir 2023a; Leftwich 2023; Rans 2023). In the UK, the Quality Assurance Agency (QAA) has argued that 'employers will expect (and value) graduates to be familiar with GenAI tools when they enter the workforce' (QAA 2023, 3). The following text extract crystallizes this idea:

> Integrating AI into the curriculum should not just be about adopting the latest technology but about preparing students for a future where AI will likely be a ubiquitous part of daily life. (Essien et al. 2024, 15)

Understanding why and how engineers are using ChatGPT can help academics make informed decisions about augmenting their curriculum to accommodate AI. Indeed, WONKHE (2025) have noted that students expect to be exposed to industry-relevant tools and technologies during their education. A study by the Organisation for Economic Co-operation and Development (Lane, Williams, and Broecke 2023) found that AI has helped employees with decision-making tasks, and if used correctly, could contribute to higher productivity and better job quality. Of course, the quest for effectiveness and efficiency is also omnipresent in HEIs and academics' professional roles and identities will no doubt face challenges going forward. The two text extracts below exemplify the current flux:

> As a community we need to understand that the technology is improving rapidly, and we need to be prepared for a very different learning environment in the next twelve to twenty-four months (Nikolic et al. 2023, 32).

> Whether AI chatbots become a faculty nightmare or just another teaching tool may ultimately come down to this: Not the state of the technology, but whether professors are allowed the time to create meaningful work for their students (McMurtrie 2022).

ChatGPT: reconsidering pedagogy

> Effecting change in higher education is like 'turning a battleship' (or a fleet of ships, in some instances), or like 'moving a graveyard' (Eckel 2002, 80).

Whilst the universal response by HEIs to the recent Covid-19 pandemic (vis-à-vis online delivery) may dispel the mantra above, the Royal Society of Edinburgh (2023, 5) has warned that 'universities can serve as powerful gatekeepers of traditional methods of qualification and assessment'. Indeed, Liu, Geertshuis, and Grainger (2020, 12) examined the adoption of new learning technologies in HEIs and found that 'academics do not adopt the technologies as readily and in ways their institutions anticipate they should'. Nonetheless, ChatGPT's arrival has disrupted the status quo and there are examples of this technology being incorporated into lecturer's lesson plans (Lem 2023), and a case study of one university's deployment of GenAI for teaching, learning and assessment (Potter, Welsh, and Milne 2023). Furthermore, in a study exploring early adopters of ChatGPT in HEIs, Mogavi et al. (2024) found that whilst some users considered it to be a transformative tool for student learning, there are also concerns about how the technology may encourage students to satisfice and engage in superficial learning habits. UNESCO (2023, 13) are upbeat on this matter – 'at least for now, ChatGPT cannot replace human creativity and critical thinking and it is on these strengths that higher education has flourished'. However, in a study of postgraduate business school students, Essien et al. (2024, 12) found that ChatGPT had aided the development of 'lower-level cognitive skills, such as understanding and application, as outlined in Bloom's Taxonomy'. Furthermore, Rivers and Holland (2023) have argued that GenAI can be used by students for higher order thinking:

> Bloom's taxonomy remains a respected method in teaching, learning and assessment design. We simply offer that when integrating generative AI to teaching, learning and assessment we should flip our approach and start with creation. Suddenly, AI becomes a partner for learning, a co-creator that might accelerate insight.

Kramm and McKenna (2023, 2) have called for HEIs to move past an instrumental approach to learning, the knee jerk reaction to ChatGPT has been a 'police-catch-punish approach'. Luo (2024, 11) recommends that universities should help students become comfortable in using GenAI and that coursework submissions could be a 'collaborative effort between the student and the AI, blending their respective strengths to produce an original piece of work'. Eaton (2023) agrees in an argument which situates the contemporary academic environment as 'postplagiarism' and within which we must come to terms with the fact that 'hybrid writing co-created human and artificial intelligence is becoming prevelant and will soon be the norm'. Supporting our students to 'ask questions', and to formulate appropriate prompts (Bacon 2023; Polverini and Gregorcic 2024), in combination with reflective practice (Mogavi et al. 2024) are considered essential for the optimal use of ChatGPT in HEIs. In a recent study of job adverts for prompt engineers the authors concluded that:

> The skills and qualifications highlighted in the job advertisements serve as a valuable guide for educational institutions. Universities, colleges, and vocational training centers should consider revising curricula to incorporate relevant skills, such as prompt engineering techniques, machine learning, and more. This would ensure graduates are well-equipped to navigate the evolving job landscape and capitalize on emerging opportunities (Kutela et al. 2023, 13).

Including prompt engineering skills into the curriculum could be enhanced through introducing students to collaborative peer reviewing, reflecting real-world engineering practice. Indeed, Kay, Husbands, and Tangen (2024) have argued that GenAI learning will involve peer interaction and dialogue with teachers, 'finally fulfilling the full promise of the flipped classroom'. However, Johnson (2024) makes an important corollary, students are not subject matter experts, and they may be unable to distinguish fact from fiction. Rudolph, Tan, and Tan (2023) employ an evocative paper title to make the same point! – '*ChatGPT: Bullshit spewer or the end of traditional assessments in higher education?* Given that AI tools can make up facts, statistics and citations, and produce plausible untruths, or 'hallucinations' (Freeman 2024; Joint Information Systems Committee 2023) our students will require significant scaffolding to enable them to undertake rigorous evaluation of their own, and their peer's work. Furthermore, it has been recommended that HEIs use authentic assessment practices that prepare students for AI workplaces (The Hack and Knight 2024; Russell Group 2023). However, a recent survey of students in the UK by the UPP Foundation (2024, 48) concluded that 'there was an explicit view that the sector was at risk of falling behind when it comes to implementing innovative methods of learning, teaching and assessment, and keeping pace with innovation, including AI, in the world of work'.

There is growing evidence of ChatGPT performing a 'guide on the side' role, as a virtual personalised tutor (Ansari, Ahmad, and Bhutta 2023; Kong et al. 2023). Naser et al. (2024, 5) 'anticipate that future ChatGPT-4 and Bard generations will be able to serve as suitable teaching assistants and guides for students and young engineers'. Indeed, Gao et al. (2024, 18) have posited that the human-like characteristics of ChatGPT 'are vital to developing a superior experience for students during their learning process'. On the other hand, Crawford et al. (2024, 12) expressed concerns about AI substituting human contact in HEIs and found that when students 'feel more socially supported from AI, they feel less supported from other people'. The UNESCO Assistant Director-General for Education provides a sobering warning for all educators:

> We must not only look at what is happening today with these technologies but also project ourselves 20 or 30 years into the future. How do we balance the need to equip young people for a human-machine society, without undermining the human mind as we outsource certain cognitive functions? We cannot afford to experiment on a whole generation. Digital innovations can – and must – be designed to protect human agency (Giannini 2023, 3).

Nikolic et al. (2023, 590) have suggested that ChatGPT can be used to set 'online quizzes with zero assessment marks to confirm threshold concepts and unlock future content'. The move from 'sage on the stage' to 'guide on the side' pedagogy is evident and various authors (Essien et al. 2024; Mogavi et al. 2024; Rasul et al. 2023; Zhou and Schofield 2024) have found that GenAI can contribute to a student-centric approach in higher education. There is a wealth of guidance (Carpenter and Simmons 2005; Goldberg and Somerville 2014; Heywood 2016; Houghton 2004) available to inform engineering academics on Constructivist pedagogies, albeit, challenging entrenched ontological and epistemic beliefs may be a bridge too far for some academics! On a dystopian note, perhaps LLMs will develop Artificial General Intelligence (AGI) and human-like behaviour, becoming capable of replacing academic jobs! However, Hofkirchner (2023, 1) examined the ontological and epistemic dimensions of LLMs and concluded that 'AI is a misnomer' and that 'from a techno-social systems perspective, neither LLMs nor AGI can be called intelligent'.

Fleet of foot: ChatGPT and engineering education

In a scoping review of digital technologies in Architecture, Engineering, and Construction (AEC), Brozovsky, Labonnote, and Vigren (2024) found that as of 2022, Chatbot remained a niche topic, with Building Information Modelling (BIM) dominating the literature reviewed. One year later, Berdanier and Alley (2023, 583) suggest their readers are perhaps 'intrigued, distressed, or horrified by AI', and warn that 'there is no use in wishing for a world without AI' (584). Menekse (2023, 580) posits that 'engineering educators need to be aware of the potential risks of AI tools before integrating them into their classrooms'. Johri et al. (2023b, 574) point out the need for engineering academics to engage in Continuing Professional Development (CPD) to ensure they learn to use AI ('especially skills such as prompt engineering') and incorporate it into their programmes.

There has been some traction in AI research in the educational research of engineering disciplines such as chemical engineering (Keith et al. 2025; Kong et al. 2023; Marquez et al. 2023; Tsai, Ong, and Chen 2023), computing engineering (Shoufan 2023), biomedical engineering (Cheng et al. 2023), mechanical engineering (Bernabei et al. 2023; Tiro 2023; Zhang, Zhao, and Haddad 2025) geotechnical engineering (Kumar 2024) and management engineering (Bernabei et al. 2023). Nikolic et al. (2023) have provided some commonsense guidance for educators through their reference to Vygotsky's (1978) concept of scaffolding:

> As engineers we need to embrace tools that make us work smarter and more efficiently. Just as we scaffolded the calculator as a tool in education, so we must with AI technology (32).

Qadir (2023) gets to the nub of the problem, the 'devil in the detail' that will require engineering academics, and students, to reconsider their ontological and epistemological beliefs about the nature of engineering knowledge, and, its assessment, in an AI world:

> 'In today's world, it is more important than ever to be able to think critically and analyze arguments, spot errors and misinformation, and make fixes when necessary' (8).

Despite the interventions noted above, it is surprising that it was not until October 2023 that the Engineering Council (2023) established an Artificial Intelligence Working Group (AIWG) to examine issues raised by the use of AI and associated implications for registration and programme recognition. Furthermore, the various sub-bodies responsible for the accreditation of engineering degrees in the UK (i.e. Civil Engineering- Joint Board of Moderators 2023) have not yet updated their accreditation guidance (Guidelines for Developing Degree Programmes – AHEP4) to incorporate guidance on AI. At a more granular level, the engineering professional institutions have prompted discussion (Mosca 2023) and have provided webinars on AI (Engineering Professors Council 2025; Institution of Chemical Engineers 2023; The Institution of Engineering & Technology 2024). Furthermore, the RAE (2024a) has prompted a debate on 'Engineers 2030', a project to identify how engineering knowledge, skills and behaviours are changing in the twenty-first century:

> Paradoxically, as artificial intelligence becomes more powerful and system approaches are applied to more complex problems, the quality of human decision-making becomes even more critical. For it is people who decide how technology is applied and thus whether its massive potential to help resolve the challenges facing civilization is realised, underused or, worse, abused. Human characteristics such as wisdom, creativity, empathy, and connection to the natural world are central to help engineers work effectively to harness the power of emerging technologies (RAE 2024a, 12).

Industry engineers role in the curriculum

> If it is intended that the curriculum should prepare engineering students for work, it is necessary to understand what qualified engineers do at work (Heywood 2016, 36).

There is a tradition in HEIs of consulting practicing engineers to inform engineering curricula (Buckley, Trevelyan, and Winberg 2022; Scott and Yates 2002) that inculcate in students the habits of mind and ways of thinking, that are consistent with professional engineers (Goldberg and Somerville 2014; Kamp 2016; Lucas, Hanson, and Claxton 2014).

Indeed, the Royal Academy of Engineering (RAE 2007, 22) recommended closer ties between academia and industry, 'to establish active, long-term relationships with university engineering departments in the area of education'. A decade later, Broadbent and McCann (2016a, 2016b) provided guidance on this matter. Furthermore, the RAE (2024b) Visiting Professors (VP) scheme can also be used to ensure that experienced industry engineers are involved in teaching programmes. Of late, the RAE (2024a) is leading the initiative 'Engineers 2030' and recognises that the future to 2050 and beyond, holds much environmental, political, and technological uncertainty. The RAE appears to recognise the need to include students views in how the profession develops:

> So, we will make a priority of engagement between young people and experienced professionals. The changes made to support young engineers will be more successful if they are informed by an intergenerational dialogue (15).

Typically, engineering departments will have an Industrial Advisory Board (IAB) consisting of local employers and Alumni who will provide varying degrees of support to ensure the curriculum is relevant. Programme Accreditation bodies such as the Joint Board of Moderators (2023, 20*)* appear to acknowledge the need for HEIs to be agile and responsive to demands from industry. The importance of Alumni in ensuring HEIs maintain a relevant curriculum is noted by several authors (Gallo 2021; Saunders-Smits and de Graaff 2012; Turnbull 2020). Of late, several authors (Buckley, Trevelyan, and Winberg 2022; Hack 2023; Naser 2022; Stephenson and Knight 2024) have all noted the importance of HEI's collaborating with industry to ensure that their AI strategies are informed by the latest developments in industrial practice.

There is some anecdotal evidence of practicing engineers using AI in the workplace (Archmaster 2023; Project Scotland 2023; Reddit 2023; Spencer 2022; UK Parliament 2023) and SEFI (2025, 1) find that 'engineering practice is increasingly mediated by disruptive emerging digital technologies.' With specific reference to civil engineering practice, Dudhee and Vukovic (2023, 150) have posited that through integrating LLMs into workflows 'the industry can unlock unprecedented levels of efficiency, creativity and innovation, propelling it into a more productive and successful future'. Testing such rhetoric has begun. Joskowicz and Slomovitz (2023) surveyed engineers, students and academics and focused on respondents with an electrical, electronic and computer profile residing in twenty countries across the Americas. Results from their survey ($N = 375$) revealed that, by a large margin, ChatGPT was the most used GenAI tool out of several options listed. In a smaller study Saka et al. (2024) interviewed seven experts in the AEC industry on opportunities and limitations of GPT models. They found that 'current applications of GPT models in the industry are for information retrieval, scheduling, and logistics'. The experts considered the limitations of ChatGPT to be 'hallucinations, accepted input formats, cost and reliability' (26). Engineers Australia (Bell 2025) gathered data from engineering professionals, educators and students on the impact of GenAI on the engineering profession in Australia. Bell concluded that 'businesses need to foster a culture of openness to AI and GenAI so that engineers feel safe to collaborate, share and explore how the technology can best be used' (3). Following these insights, we want to ask more specifically: *What exposure have engineers in industry had to ChatGPT and how can this knowledge help us to inform our engineering programmes?*

Research methodology and online survey design

The study was approved by the University's ethics committee and complies with the requirements of the British Educational Research Association (2018) Ethics Guidelines. Table 1 provides an abbreviated overview of online survey design aiming to guide presentation of analysis in the paper.

The design has 17 questions and an estimated 10-minute completion time. Multi-select Qs 12, 13, 15 and 16 are coded as sets of nominal yes/no responses (N2) making a total of 41 items and 12 scales.

Survey themes were: 1. Embeddedness (EMBD) of ChatGPT within practice (Q12, Q13); 2. Positive Impact (PI) of ChatGPT on work performance (Q14, Q15); 3. Apprehension (APP) of ChatGPT on practice (Q16), and; 4. Potential Value (PV) of ChatGPT to organisations (Q17). Categorical (Non-Linear) Principal Component Analysis (CATPCA in SPSS software) (Linting et al. 2007) was carried out to explore the possibility that the 26 items of the survey could be adequately described by a smaller set of dimensions, potentially related to the survey design themes. This analysis is included as Appendix 2, but as inconclusive, the majority of results discussion remains at the original item level.

Table 1. Survey design structure showing abbreviated question themes. ^{NX} or ^{OX} indicates 'nominal' or 'ordinal' data scale where X is the number of response items in the scale.

Respondent Profile, n = 86 (All respondents)				
Q1. Job Discipline^{N11}	**Q2.** Role Description^{N5}	**Q3.** Business Size^{O4}	**Q4.** Role Level^{N7}	**Q5.** Age^{O5}
Q6. Gender^{N5}	**Q7.** Do you have experience using ChatGPT for work purposes?^{N2}			
ChatGPT User Profile, n = 55 (Work based ChatGPT Users only)				
Q8. How did you find out about ChatGPT?^{N4}	**Q9.** When did you first hear about ChatGPT?^{O3}			
Q10. How often do you use ChatGPT?^{O5}	**Q11.** Is your employer aware?^{N2}			
Embeddedness (EMBD) of ChatGPT, n = 55 (Work Based ChatGPT Users Only)				
Q12. I use ChatGPT to (select all that apply):	12.1 Check/review human work^{N2};	12.2 Start task^{N2};		
12.3 Start and finish task w. human checking^{N2};	12.4 Start and finish tasks, no human check^{N2};	12.5 Other^{N2}.		
Q13. I use ChatGPT for (select all that apply):	13.1 Core engineering tasks^{N2};	13.2 Supporting Research^{N2};		
13.3 Client and colleague communication^{N2};	13.4 Organisation, prioritisation or task scheduling^{N2};	13.5 Other^{N2}.		
Positive Impact of ChatGPT (PI) n = 55 (Work Based ChatGPT Users Only)				
Q14. Over the next 12 months, I envisage that ChatGPT will have … … impact on my work:^{O5} **(impact on work scale)**				
Q15. What improvements do you see ChatGPT enabling in your work? (select all that apply, or leave blank):				
15.1 Efficiency^{N2};	15.2 Quality^{N2};	15.3 Scope (knowledge access)^{N2};	15.4 Creativity^{N2};	15.5 Other^{N2}
Apprehension about work based ChatGPT use (APP), n = 55 (Work based ChatGPT Users Only)				
Q16. Do you have any concerns relating to using ChatGPT for work? (Select all that apply, or leave blank):				
16.1 Diminished responsibility^{N2};	16.2 Diminished job satisfaction^{N2};	16.3 Loss of 'human touch'^{N2};		
16.4 Reduction quantity of jobs^{N2};	16.5 IP leaks^{N2};	16.6 Mistrust/misuse of ChatGPT^{N2};		16.7 Other^{N2}.
Potential Value (PV) of ChatGPT, n = 86 (All respondents)				
Q17.1 UK employers are underutilising ChatGPT^{O5}	**Q17.2** ChatGPT can provide value to organisations^{O5}			
Q17.3 ChatGPT Training is required in organisations^{O5}	**Q17.4** ChatGPT is capable of useful outputs^{O5}			
Q17.5 Capability will substantially increase^{O5}	**Q17.6** ChatGPT will be useful in achieving UN SDGs^{O5}			
Q17.7 UK undergraduate programmes should incorporate ChatGPT into learning and assessment practice^{O5}.				

The call to participate adopted a random sampling technique distributing through professional social media networks. We aimed to attract engineers employed in sectors that reflect our eight Faculty of Engineering departments. It was also envisaged that the questionnaire could attract software engineers acknowledging a call for 'research conducted by members from multiple, different academic departments … to advance the knowledge of the use of AI in more disciplines' (Crompton and Burke 2023, 180).

The anonymous survey was conducted via the University's Qualtrics account in compliance with General Data Protection Regulations (Qualtrics. 2020). The data was exported in.xlsx format, cleaned and coded as shown in Table 1 and then transferred to IBM's SPSS software for analysis. Coding is with respect to the positive response (1 = yes, 0 = no, 4 = strongly agree … … 0 = strongly disagree).

To accompany recurring references to measures of association between parameters, Table 2 provides an overview of the measures used in analysis (Khamis 2008).

Despite 33 respondents expressing willingness to participate in focus groups, few completed the contact form, and one 30 min focus group with 3 engineers took place. A cursory analysis of the ZOOM transcript allowed some additional interpretations provided in the discussion below in the focus group section.

Sample, survey reliability and respondent and user profiles

Of 163 responses initiated, 86 completed with 55 indicating experience of work-based ChatGPT use and answering all questions. There was bordering 'acceptable' scale reliability KR-20 = .65 across 7 yes/no nominal items for the embeddedness section of the survey (removing Q12.5, 13.2, 13.5) and KR-20 = .6 across each of Q15 (Q15.6 removed) and Q16 (Q16.7 removed). Cronbach's Alpha for the 5-point agreement scale of Q17 (n = 86) related to Positive Impact is $\alpha = .80$; 'good' ordinal scale reliability (Nunnally and Bernstein 1994).

Figure 1 shows the sample breakdown by engineering discipline and role type. The disparity in response size between the top five ('Design, Manufacturing and Management' combining 3 survey choices of Product Design 6/7.1%, Manufacturing 9/10.6% and Engineering/technology/operations management 4/4.7%) and other disciplines may reflect lead authors profiles and their leverage of partnering employers. Job role titles are not monolithic within industry; In civil engineering there is clear delineation between those who work in a consultant design role, and those who work 'on site' (contractors). These labels appear less prevalent outside civil engineering and the often selected 'other' choice suggests respondents struggled to select pre-defined terms.

Figure 1 also shows the relative use of Chat GPT within the disciplines and role levels. It is notable that uptake for EEE and Design Manufacturing and Management was lower despite relatively high respondent numbers, but this could be sample related rather than a disciplinary trend.

Figure 2 shows respondents by employer size, the majority employed in large organisations with over 251 employees.

Figure 2 shows at least 50% of each respondent grouping (63.9% overall) claiming to have used chat GPT in work. Such consistency suggests a general level of uptake in the engineering industry. Only age (Q5) has a significant, albeit weak, association ($r_s = .23$, $p = .03$) with uptake (Q7) where Table 3 and Figure 3i show that between ages 21–45 the majority have used ChatGPT at work, with the highest uptake for the 21–30 group.

The adoption of ChatGPT by Millennials and Gen Z engineers offers employers an opportunity to capitalise on their expertise, disseminate new knowledge within their organisations, and develop competitive advantage:

Table 2. Chosen measures of association for different data types/levels.

	Ordinal (o)	Continuous (c)	Nominal (n)
Nominal (n)	Kruskal Wallis H (>2 levels)	Pearson, r	Cramer's V
Continuous (c)	Kendall's Tau, τ	Pearson, r	Pearson, r
Ordinal (o)	Spearman, r_s	Kendall's Tau, τ	Spearman (2 levels), r_s

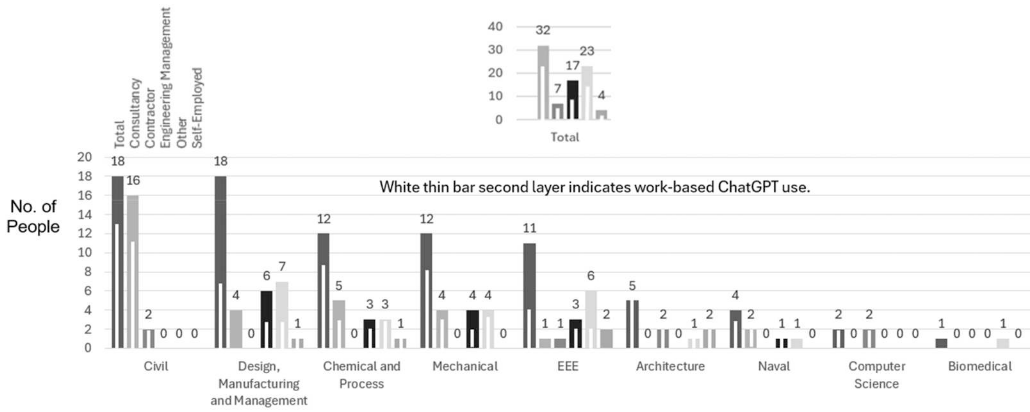

Figure 1. Respondent disciplines, role type and work-based ChatGPT use.

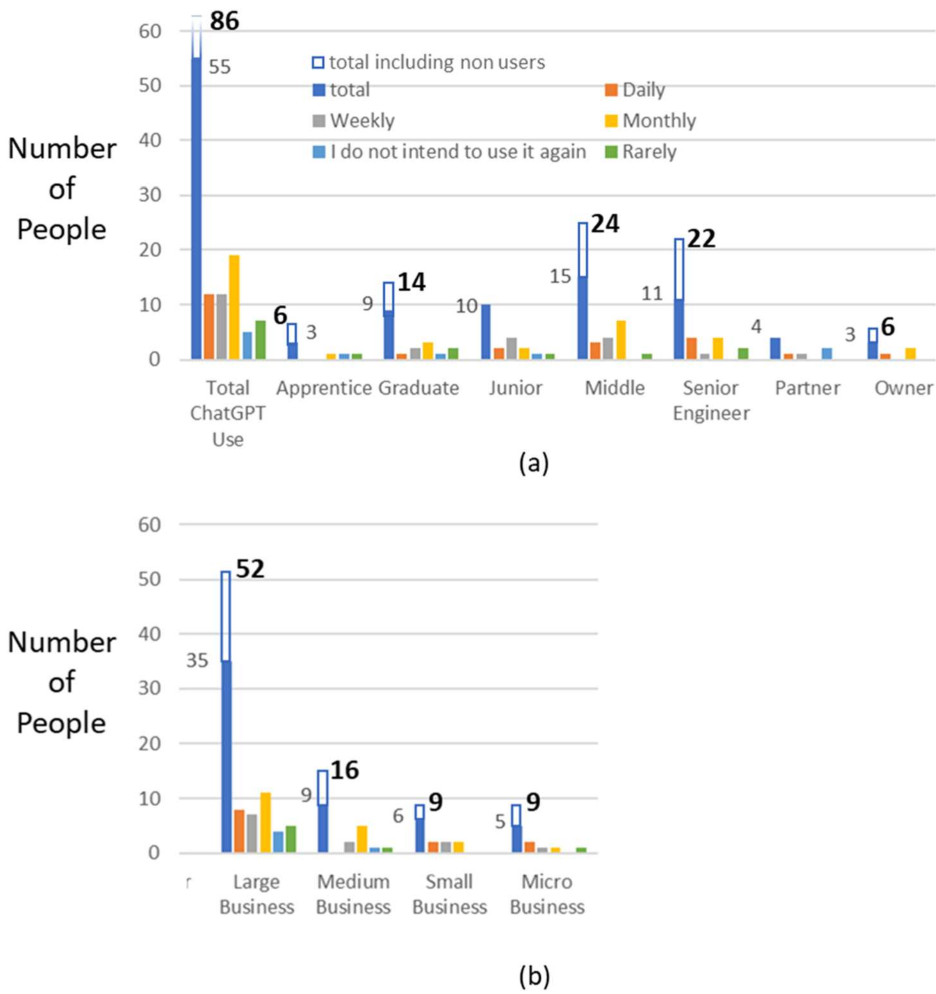

Figure 2. Chat GPT use across business size and role descriptor.

Table 3. Association Matrix highlighting possible relations between survey respondent profile and work-based ChatGPT use.

		Association Matrix (N = 86)							
	Variables	N	N	O	N	O	N		
		Q1	Q2	Q3	Q4	Q5	Q6		
N	Q7	0.37	0.23	0.08	0.35	**−0.23***	0.09		
		Association Matrix (N = 55)							
	Variables	N	N	O	N	O	N	O	N
		Q1	Q2	Q3	Q4	Q5	Q6	Q10	Q11
N	Q8	0.45	0.32	0.4	**0.42***	0.7	0.17	2.4	0.19
O	Q9	13.1	2.14	0.04	3.4	−0.06	−0.1	0.22	0.06
O	Q10	0.14	0.04	−0.09	8.37	0.14	0.17		
N	Q11	0.46	0.22	**0.34***	0.3	2.7	0.1		

Notes: *.$p < 0.05$ level (2-tailed). **.$P < 0.01$ Level (2-tailed). C = continuous, O = ordinal, N = nominal

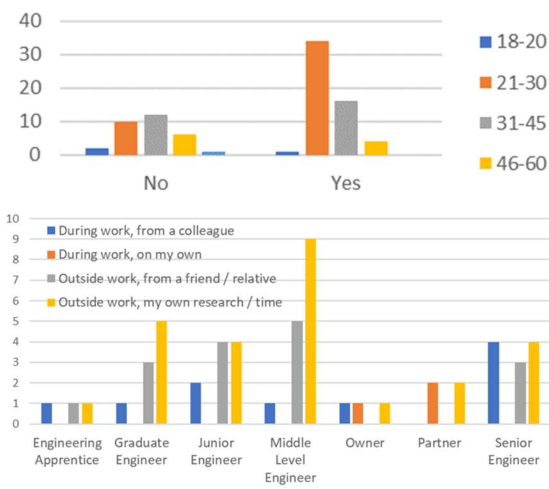

Figure 3. i. Q5 against answers yes/no to Q7 ii. Q4 against Q8.

> Recent graduates and current students are primed to help companies implement generative models and reskill colleagues. With proper training, mentorship, sponsorship and support, early talent can rapidly disseminate their AI expertise throughout organisations (Handshake 2023, 7).

Figure 2 also shows use frequency (Q10) varying across employer size and role level. Monthly is the most common pattern demonstrating that Chat GPT is yet to reach uptake levels we assume for popular search engines (also increasingly AI driven). However, when combing daily and weekly users, it is clear that the majority of work-based users are more regular than monthly. Mid-level and senior position engineers use ChatGPT more often (66.6% and 70% at least weekly) than junior and graduate professionals (40% at least weekly). This raises the interesting hypothesis in regard to the adoption of AI technology, and of the frequency of use being correlated with the formal authority (and a gatekeeping role) and the confidence level and/or experience of the professional. Senior engineers will have accumulated tacit knowledge, leadership, and management experience, and will be cognizant of the legal, commercial, and reputational risks related to introducing new technology into their organisations. Of note, Bell (2025, 3) found that in Australia, 'senior engineers tend to leave it to the next generation to see how GenAI could be incorporated into their work.' Going forward there is further scope to understand the 'psychological factors' related to engineers' adoption of new technology (Roberts et al. 2021) and in particular, how AI anxiety (Kaya et al. 2024) may hinder adoption.

Table 3 and Figure 3ii show potentially significant, moderate, association (V = .42, $p = .04$) between role level (Q4) and how users found out about ChatGPT (Q8). It is interesting to note the general trend of most users coming to ChatGPT outside of work, and most commonly without perceived as self-discovery. Work-based ChatGPT use therefore did not seem particularly community driven, although not hidden with 39 (70.9%) claiming their employer was aware of ChatGPT use (Q11, Table 4). However, there is no statistical association between responses to Q8 and Q11 ($V = .19$, $p = .6$).

Given that AI can infiltrate the workplace through both formal and informal means our questionnaire sought to uncover possible covert practices by employees. Table 3 shows a significantly weak correlation between business size ($r_s = .34$, $p = .01$) and whether employers are aware of ChatGPT use. The most common response in the sample (71%) was that employers are aware in all business sizes, but all instances of employers being unaware were from respondents in medium and large businesses. There seems no rationale to assume employees are more or less scrutinised in larger organisations.

No other significant association between Q11 and any descriptive respondent item (Q1-6). The introduction of AI and LLM's in the workplace remains fluid and in a study on employers and employees use of AI (Hays 2023) it was found that employers were monitoring or banning AI tools in the workplace.

For the 29% of respondents who are engaging in covert use of ChatGPT this has potential to cause legal, commercial, and reputational risks for their employers. It can be assumed that there could be employee disciplinary issues with such work. Known as shadow IT / Grey IT working (National Cyber Security Centre 2023) it involves employees using unofficial measures to complete their work. Given that in a post Covid-19 world many engineers now work part time, from home, it may be easier for employees to deceive their employers when out of sight, perhaps undertaking work tasks by iterating between personal and employer owned information technology.

In terms of gender, Table 3 shows there are no significant associations related to gender (Q6) in the data. A higher portion of the female respondents (71.4%) confirmed that they had used ChatGPT at work in contrast to male (62.3%). A higher portion of males (46%) were at least weekly users in contrast to 40% female, but this is not significant especially given the male sample is more than double the size of the female.

Table 3 shows all measures of association between Q1-6 and Q7-11, and whilst there appear further moderate association values (Cramer's V tends to produce higher association figures than Pearson or Spearman), none of these are significant relationships beyond the two highlighted.

Appendix 1 includes a full association matrix showing all significant relationships between survey items. The preceding section utilises these associations in category analysis to explore reduction of the survey items into themes.

Survey themes

The design aimed to operationalise four survey themes — Embeddedness, Positive Impact, Apprehension, and Potential Value — as data dimensions through a reduction exercise. Convergence on a singular solution showing 4 (3 or 5) dimensions adequately describing the data proved challenging, but item values for the four dimensions (EMBD, PI, APP, PV), were summed for each respondent and utilised within a correlation matrix (Table 5). In Appendix 2 detailed results are included for CATPCA (Linting et al. 2007) which followed principles and steps set out for Exploratory Factor Analysis or PCA by Samuels (2017). To deal with the split survey path and small sample size (Hair et al. 1998), the analysis was partitioned (P1 = Q12-16, n = 55; P2 = Q17, n = 86). In addition, the sample was bootstrapped (1000 samples, Bias Corrected and Accelerated, BCa, 95% confidence intervals).

Table 4. Q11 Is your employer aware of your use of ChatGPT? (n = 55).

	Select one answer only:	% Respondents	No. Respondents
0	No	29.1%	16
1	Yes	70.9%	39
		Total	55

The table in Appendix 2 shows the non-bootstrapped 3-dimension solution for P1 has marginally acceptable total % Variance Accounted For (VAF, 51.13% – acceptance threshold typically 50%) but dimension 3 having $\alpha<.55$. The bootstrapped 2-dimension solution has better α (.8 and .62), but unacceptable VAF (43.37%), increasingly so if negative loading outlier item Q15.5 is removed. Therefore P1 CATPCA is inconclusive and it is troublesome to suggest that the 19 items are adequately explained by a smaller set of dimensions. It does seem more reasonable to suggest that a single dimension (PV) could explain P2 where all items are retained ($\alpha = .85$, VAF = 53.92%). Given this ambiguity in the CATPCA and the significant and moderate correlations between EMBD and PI, EMBD and PV, and PI and PV shown in Table 5, it is difficult to suggest the data is adequately described by the 4 themes alone; item level analysis and discussion is required.

Results & discussion

Table 5 considered associations between independent user profile variables Q1-11 and (potentially) dependent variables EMBD, PI, APP, PV. Discussion of all variables is organised around these themes and Table 5 is a recurring reference throughout the following sections.

Embeddedness (EMBD) of ChatGPT in working practice

Embeddedness (EMBD) sums Q12-13 for respondents (no = 0, yes = 1). The mean is 3/7 (42.8%) and SD = 1.85 suggests ChatGPT tended to be most often applied in more than 1 type of task, and to generate and/or check content, but fewer people using it in a highly variable way in their role. Perhaps not surprisingly, there is a moderate correlation ($r = .49$, $p = <.000$) for EMBD with frequency of ChatGPT use (Q10).

Digging into the components of EMBD and following on from uptake data shown in Figures 1 and 2, Table 6 shows that the majority of users had used Chat GPT as a ‘landscape’ type feature to enable them to understand the contours of the task in hand. Providing a surrogate, critical ‘brainstorming’ friend that can perhaps point to omissions in human cognition. Not only was this the most common selection amongst all participants but, was also often (34.5% of respondents) selected as the only purpose that ChatGPT would be used for. Whilst we did not include the term ‘prompt’ in our questionnaire, in Table 4 both the second and third most popular responses are indicative of using ChatGPT as a ‘checker’. It is then perhaps surprising that twelve respondents claimed to have used Chat GPT to complete a task without modification, although reassuring that this is the least likely application from the options, particularly given that there is a general awareness that LLM’s can make up facts, statistics and citations, plausible untruths, or ‘hallucinations’ (Freeman 2024; Joint Information Systems Committee 2023). It is surely unwise, and perhaps unprofessional, to have such confidence in this technology at this point in time. From ‘other’ respondents included free text responses classified under one of: ‘As a clever search engine for research and translations’; writing or rewriting communications/text; debugging and/or suggesting coding and idea generation.

In Table 7 it can be seen that the majority of participants used Chat GPT to undertake research to support tasks. Information mining the engineering disciplines Body of Knowledge (BOK) has typically involved consulting books, journal proceedings, reports, codes of practice etc., and of course consultation with peers and other experts. Given that Chat GPT can fabricate scientific articles (Májovský et al. 2023) there is a risk that the engineering BOK will become polluted with untrustworthy data. Practicing engineers rely on both explicit and tacit knowledge to undertake their work, a ‘knowing that’, and ‘knowing how’. Typically characterised as ‘hard’ knowledge and ‘soft’ skills. Contemporary thinking considers them in combination- professional skills. This is an important issue given that 19% of the respondents used Chat GPT for ‘Core engineering tasks relating to my profession’. In retrospect it would have been insightful to have enquired about specific use of Chat GPT in the different phases of an engineering project (i.e. brief-design development-manufacture-recycle) and associated tasks.

Table 5. Correlation matrix showing associations between 4 dimensions of the study.

Variables		Mean	SD	N Q1	N Q2	O Q3	N Q4	O Q5	N Q6	N Q7	N Q8	O Q9	O Q10	N Q11	C EMBD	C PI	C APP
				Pearson (r) Correlation Matrix (N = 55, except PV86, N = 86)													
C	EMBD	3.00	1.85	0.18	0.25	−0.21	0.16	0.122	−0.084	–	0.04	−0.24	**0.49****	0.15	1		
C	PI	4.0	2.3	−0.08	0.218	−0.08	0.217	0.217	0.06	–	−0.05	−0.09	**0.65****	0.12	**0.58****	1	
C	APP	3.98	1.46	−0.04	0.12	−0.08	0.17	0.08	−0.007	–	−0.11	−0.16	0.02	−0.06	−0.13	0.21	1
C	PV	19.54	4.98	0.07	−0.17	−0.01	0.21	0.17	−0.15	–	0.09	0.12	**0.43****	0.02	**0.44***	**0.6****	−0.07
C	PV86	26.27	4.89	−0.06	−0.034	−0.134	0.06	−0.00	0.06	0.07							

Notes: *.$p < 0.05$ level (2-tailed). **.$P < 0.01$ Level (2-tailed). C = continuous, O = ordinal, N = nominal

Table 6. Respondents task type use of ChatGPT at work (n = 55).

	Q12 select all that apply:	% Respondents	No. Respondents
1	Check / review work already completed by a human- did I miss something	29.1%	16
2	Start a new task- use Chat GPT to provide a broad view of the landscape to assist task completion by human.	67.3%	37
3	Start a new task- use Chat GPT to complete the task, then undertake a brief 'ballpark' check.	30.9%	17
4	Start a new task- use Chat GPT to complete the task alone without modification.	12.7%	7
5	Other, please specify:	21.8%	12

Positive Impact (PI) of ChatGPT on practice

Positive Impact (PI) sums Q14-15. The mean is 4.05/8 (50.6%) and SD 2.3 suggests respondents held multifaceted views on impact of ChatGPT on their work, but that there were notable limits to the range of the impact. Again, it appears logical that there would be at least moderate correlations between PI and frequency of use (Q10, r = .65, p = <.000) and Embeddedness (EMBD, r = .58, p = <.000) i.e. continued use is unlikely without perceiving the possibility of positive results from ChatGPT application. However, length of use/awareness (Q9) does not clearly associate to embeddedness (EMBD, r = −.24, p = 0.08).

Beyond the overall PI associations, the responses in Table 8 demonstrate that engineers like efficiency! Completing the same work in less time is considered an opportunity for generating higher profits. Whilst this journal is not the place for a detailed argument on capitalist economics and the blue – and white-collar workers, the use of ChatGPT does raise some ethical issues related to work life balance, welfare, and employment. The questions in Table 7 relate to efficiency, quality, scope, and creativity, everyday issues for engineers at work. Whilst our participants are on the whole positive on how ChatGPT can improve their work tasks, there are some unconsidered impacts. Foremost could be AI's impact related to 'changing job content, skills needed, and the jobs being displaced' (RAE 2024a, 7), albeit, correspondingly, new specialist skills (i.e. prompt engineering) may proliferate and result in new jobs. One of our participants offered a succinct opinion (other response) in relation to how ChatGPT has shaken the engineering industry, and its potential to transform what they considered to be an industry in stagnation:

> The impact is so huge, it can make the difference between AEC industry remaining as docile as it has been over the last 100 years, or actually transform into a 21st c. industry. Noting lack of skills to use the existing technology has been one of the key reasons behind the slow transformation of this industry.

Apprehension (APP) of ChatGPT impact on working practice

Apprehension (APP) sums Q16 components with mean 3.98/6 (49%) and low SD (1.34). Users agree to multifaceted concern about ChatGPT impacting work/profession integrity. However, there are no notable associations for this combined measure, even if removing the items problematic during CATPCA. If it is a genuine dimension, this may suggest that more extensive users, or those with more positive outlooks, did not have notably lower apprehension than those using less extensively. Future qualitative work could focus on users', organisational or disciplinary tendency for risk perception and aversion.

Table 7. Respondents application of ChatGPT at work Responses ($n = 55$).

Q13 select all that apply:		% Respondents	No. Respondents
1	Core engineering tasks relating to my profession	38.2%	21
2	Research purposes to support tasks	67.3%	37
3	Communication between clients and colleagues	36.4%	20
4	Organisation, prioritisation, or scheduling of tasks	18.2%	10
5	Other, please specify:	10.9%	6

Table 8. Responses (*n* = *55*) how ChatGPT can Improve their work tasks.

	Q15 Select all that apply:	% Respondents	No. Respondents
1	Improved efficiency (more work completed in the same amount of time)	61.8%	34
2	Improved quality (higher quality outputs completed in the same amount of time)	40%	22
3	Improved scope (larger area of knowledge & easier access to information)	50.9%	28
4	Improved creativity (higher quality & quantity of ideas)	38.2%	20
5	Other, please specify:	4.59%	5
			109

Looking deeper at the components of the APP dimension, Table 9 shows the components that respondents could align with. As one participant commented in the 'other' section – *It gives wrong and errant information. It cannot be trusted. Garbage in = garbage out as well as good in = still garbage out + checking time!* Practicing engineers use their intuition (Miskioğlu et al. 2023) to undertake 'ballpark checks' on computer outputs. This intuition is perhaps a mix of experience, engineering judgement, pragmatism, and an accumulation of tacit knowledge. All of which are generally lacking in novice students and graduate engineers! Indeed, in relation to quality assurance, Bearman et al. (2024, 4) posits that students will need help to develop their evaluative judgement capabilities when using GenAI tools, this will include helping them to judge 'the quality of a text produced by ChatGPT'.

Our respondents are correct to be wary of the ethical and moral responsibility risk associated with LLMs. Humphreys et al. (2024) have provided a comprehensive account of the risk to businesses when they fear falling behind competitors in a race to implement GenAI. They 'identify two examples of ethical concern, overreliance, and over-trust in generative AI, both of which can negatively influence business decisions, leaving companies vulnerable to cyber security threats' (1). In regard to the professional and ethical behaviour of engineers the professional institutions are on catch up when it comes to the use of AI. In a landmark report by the RAE (2022) *Engineering Ethics: Maintaining society's trust in the engineering profession,* only a cursory glance was made to the use of AI by engineers. Of late the RAE (2024a) has fully acknowledged the potential and risk of GenAI for engineering and society.

It is pertinent here to consider the role of computer technicians and software engineers within engineering organisations. No doubt they have had a heightened strategic and operational presence since AI has become more prominent in businesses, particularly since the arrival of LLMs. Whilst the British Computer Society (2022) seek to professionalise this profession though their own code of conduct for members, there is a danger that this discipline suffers from negative and stereotypical portrayals of IT workers, vis-à-vis the British television sitcom *The IT Crowd* (García-Crespo, Colomo-Palacios, and Miguel-Gómez 2008). If AI is to be a dominant tool for engineers, then the in-house interdisciplinary collaboration between engineers and IT professionals may require a more nuanced relationship to ensure synergy is achieved.

Potential Value (PV) of ChatGPT to organisations

The mean for Potential Value (PV) summing Q17 was 19.54/35 (55.8%); users could agree to some level of value for ChatGPT to organisations but with higher variability in that agreement than

Table 9. Responses (*n* = *55*) concerns relating to using ChatGPT for their work.

	Q16 Select all that apply:	% Respondents	No. Respondents
1	Diminished human responsibility/accountability	15.60%	17
2	Diminished job satisfaction	3.67%	4
3	Loss of 'human touch'	12.84%	14
4	Reduction in quantity of jobs	1.83%	2
5	Intellectual property leaks	26.61%	29
6	Mistrust/Misuse of ChatGPT	33.94%	37
7	Other, please specify:	5.50%	6
			109

other measures (SD = 4.98). These scores have a moderate correlation with EMBD (r = .44, p = 0.001) and stronger with PI (r = .6, p = <.000) suggesting that those with a wider usage and seeing greater payoff are logically holding different views on future value for the software.

Looking at PV for the full n = 86 sample (PV86) the mean is higher at 26.27 (75%) and there is no association between how respondents perceive value of ChatGPT and Q7; whether or not they use it for work purposes (r = .07, p = .53). This suggests that respondents who do not use ChatGPT for work purposes do not necessarily perceive lower value in the tool than those that do use it, and with no association between APP and PV, it does not seem that apprehension is preventing use of ChatGPT, at least in this sample (Kaya et al. 2024). It is interesting to note that the strongest agreement (52.3%) for any of the PV component questions is for Q17.3 'training is required to best use ChatGPT in engineering organisations'; could a lack of awareness of ChatGPT capability and application be the main barrier to use?

Reflecting on whether higher education would have a role to play in training, we turn to Q17.7 which asks respondents to agree to 'UK undergraduate engineering programmes should incorporate ChatGPT into learning and assessment practices'. Whilst there is 82.5% agreement that training is required, there is lower total agreement (55.7%) that the tool should be embedded in university courses. This lower level could be for a variety of reasons; concern over depth of learning and academic integrity, belief that it is not the role of universities to provide training on niche and nascent tools or simply that the kind of training required is best provided within the context of a role. Indeed, Bell (2025, 25) found that in Australia, 'tertiary education institutional policies on embracing GenAI to enhance learning have lagged' and that concerns over the negative aspects of GenAI 'can hinder the willingness of some to embrace the tools in an educational setting' Nonethless, 55.7% of our respondents agreed that their is potential value in training students in the use of GenAI tools.

Our findings in PV are perhaps self-confirming in that since the data was collected (Table 10), the capabilities of ChatGPT have increased (Q17.5, 71% strongly agree-somewhat-agree) and there has been a growth in calls for employers to ensure their workforce are trained in its use (Q17.3, 84% strongly agree-somewhat-agree). Correspondingly, there has been a general recognition that ChatGPT can add value to an engineering business (Q17.2, 76% strongly agree-somewhat-agree), albeit with a cautionary caveat as noted above.

Given the importance of engineering's role in addressing the UN Sustainable Development Goals (SDG's) we speculated that our respondents would see a role for ChatGPT. However, 42% of respondents (neither agree nor disagree) and 18% (strongly disagree-somewhat disagree). Nonetheless there are others (Wang et al. 2023) who have argued that ChatGPT can contribute to the aims of the SDGs.

Focus group

In regard to the focus group interview with three engineers the participants felt there was clear value to be had from formal ChatGPT training, stating that having experience or training in its use noticeably improves the output quality of generated text. The general opinion was that ChatGPT will enhance student's abilities to learn and complete coursework, which requires some level of response from assessment design and planning.

Participants believed ChatGPT use is not something which needs to be compulsory as part of university studies, though guidance on its proper use should be available to students and teachers.

Another key discussion point was how ChatGPT and ChatGPT experience affects the job market and graduate prospects. While training or experience with ChatGPT is useful.

skill for graduates to increase their competitiveness, participants did not believe it is a core skill required for jobs within the engineering industry. A solid foundation of engineering knowledge was seen to be more valuable, as without this the use of ChatGPT was deemed untrustworthy given the risks of false information without the ability to properly review outputs. The emergence and rapid improvement of this new technology was seen to have a small risk to replace certain roles, though new roles utilising ChatGPT may also emerge to replace these losses.

Table 10. Likert questionnaire results.

Statement	Strongly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Strongly Agree	Total
Q17.1 UK engineering employers are under-utilising ChatGPT.	3.49%	12.79%	33.72%	37.21%	12.79%	86
Q17.2 ChatGPT can provide value to an engineering organisation/engineering employers.	1.16%	4.65%	18.60%	46.51%	29.07%	86
Q17.3 Training is required to best use ChatGPT in engineering organisations.	2.33%	4.65%	9.30%	31.40%	52.33%	86
Q17.4 ChatGPT is currently capable of producing useful outputs.	5.81%	3.49%	25.58%	43.02%	22.09%	86
Q17.5 The capabilities of ChatGPT will substantially increase in the next 24 months.	2.35%	3.53%	23.53%	21.18%	49.41%	85
Q17.6 ChatGPT will prove useful in achieving the UN Sustainable Development Goals.	4.71%	12.94%	42.35%	28.24%	11.76%	85
Q17.7 UK undergraduate engineering programmes should incorporate ChatGPT into learning and assessment practices.	9.52%	13.10%	20.24%	30.95%	26.19%	84

Conclusion

The premise of our research was that we can inform the introduction of LLM's within our engineering curriculum through understanding how practicing engineers are adopting this technology. There are however contextual and nuanced differences between engineering workplaces and academic learning spaces. Seeking to introduce an authentic curriculum that reflects engineering practice can only ever be achieved in part. Of course, students enrolled on our Graduate Degree / Degree Apprenticeship programmes, and students who secure summer / year out placement, will immerse themselves in industry practice and may have opportunities to use LLMs. Nonetheless, the novel aspect of ChatGPT and the relative ease of access for users exemplifies the informal nature of its use, both by engineers in our study, and by students as indicated in the studies cited in this paper.

The overarching conclusion from our research relates less to the practicalities of ChatGPT use in the engineering planning, design, and manufacture process, but on how engineering employers adopt new AI technology as an aid to improve their effectiveness and efficiency, operational practice, and ultimately to aid their competitive advantage. Related to this is a paucity of research on AI's relevance to Organizational Learning (OL) and Knowledge Management (KM) within businesses. Nonetheless, our findings suggest that our respondents' use of ChatGPT encompassed corporate level risk-reward decisions with considerations related to commercial and reputational performance. In academic terms, this appears to be aligned to a parallel issue of what can be considered 'macro pedagogy' issues. Johri et al. (2023b, 574) capture this:

> With information in conversational form at our fingertips, and those of our students too, questions such as 'what are we teaching,' 'why we are teaching it,' and 'how can we best teach it' become even more urgent.

In the research methodology section of this paper, we made readers aware that we were unable to follow through with the focus group interviews. These were intended to explore the issues raised by Johri et al above. Whilst we do not have sufficient interview data to interpret, it is possible to speculate on where engineering industry and academic use of ChatGPT converge. There may be cross over learning whereby students engage with LLMs in curricular, co-curricular and extra-curricular learning.

While the data collected, analysed, and presented above remains limited in scope and scale, there are clear trends which emerge that can help us answer our research question- *how can this knowledge help us to inform our engineering programmes?* The results of the Likert Questionnaire reveal the general sway of respondents' opinions on the value ChatGPT can bring, and thus the degree of

ChatGPT teaching implementation within engineering degrees. That is, ChatGPT was generally seen in industry to be able to bring value when used correctly and ethically and should thus be introduced to students as a tool in this way.

A final thought

In the ground floor corridor of our engineering faculty building, two maxims are displayed in large lettering on the walls (below). We are unsure who commissioned the artwork, or indeed the purpose. However, it can be assumed that the text is intended as a stimulus to inspire and motivate engineering students and staff alike.

> If I have seen further, it is by standing on the shoulders of Giants. (Isacc Newton).

> One machine can do the work of fifty ordinary men. No machine can do the work of one extraordinary man. (Edward Hubbard).

Setting aside theoretical concepts of 'habituation' (a diminished response to a repeated stimulus) it is appropriate to reflect on both quotations through a GenAI lens, an interplay between human and machine learning. The RAE (2024a, 12) have put their faith in human intervention as we move forward with AI:

> As in previous periods of rapid technological and societal change, such as the Renaissance, the leaders who emerge are often polymaths whose knowledge and abilities span a wide range of areas.

However, the future is unwritten, perhaps by 2050 it may be that both the giants and extraordinary men may be replaced by a homage to non-human intelligence. Albeit it is questionable if historians of engineering will write hagiographic accounts of machines!

Limitations

There has been an intermission of twenty months between collecting the primary research data, completing the paper, and passing through the peer review process. In normal circumstances this would not be unusual for engineering education research. This is not the case with ChatGPT. It has gone through two revisions since we collected our data, and it has no doubt further permeated engineering workplaces over the piece. Despite the rapid proliferation of this technology within education and industry, we are in a formative period of its development. Our research should be considered in this light. It is a 'snapshot' of an evolutionary period in 2023 when engineering employees were beginning to grapple with this new technology. Replicating the research in 2025 may elicit data demonstrating wider use of ChatGPT by engineering employees and their employers, but not necessarily so (Fletcher and Nielsen 2024).

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Appendices

Appendix 1. Full association matrices

		N	N	N	N	N	N	N	O	N	N	N	N	N	N	O	O	O	O
		Q8	Q11	Q12.2	Q12.3	Q12.4	Q13.1	Q13.4	Q14	Q15.1	Q15.3	Q15.4	Q16.3	Q16.4	Q17.1	Q17.2	Q17.3	Q17.4	Q17.6
N	Q1						.69**												
O	Q3		-.34*	-.3*				-.33*											
N	Q4	.43*																	
O	Q5			.29*					.37**								.28*		.32*
N	Q6									.34*			.27*						
O	Q10				0.44**	.31*	0.57**		.6**	0.47**	0.34*	0.4**			.3*	.43**		.42**	.27*

		N	N	N	N		N	N	N	N	N	N	N	N	N	O	O	O	O	O	O
		Q12.4	Q13.1	Q13.3	Q13.4	Q14	Q15.1	Q15.2	Q15.3	Q15.4	Q16.2	Q16.3	Q16.4	Q16.5	Q16.6	Q17.1	Q17.2	Q17.4	Q17.5	Q17.6	Q17.7
N	Q12.1		.4**	.35*	.43**					.4**	.35**			.26*							
N	Q12.2				.33*		.38**		.32*								-4**	.44**			
N	Q12.3	.34*	.44**				.28*	.38*	.26*	.37*										.36**	.32*
N	Q12.4		.37**				.3*			.37**		.38**							-.28*		
N	Q13.1					.51**	.46**			.38*							.41*	.3*			
O	Q14						.44**		.3*	.37*						.41*	.58**	.42**		.4**	.38*
N	Q15.1									.31*							.33*	.48**		.35*	.36*
N	Q15.2								.36*	.35*							.33*			.29*	
N	Q15.3									.4*						.27*	.37*			.3*	
N	Q15.4													.27*		.41**	.52**				.3*
N	Q16.1										.3*		.39*	.43**	.32*						
N	Q16.2												.4*								

Notes: *.$p < 0.05$ level (2-tailed). **.$P < 0.01$ Level (2-tailed). O = ordinal, N = nominal

Appendix 2. CATPCA process and results

Analysis was partitioned (19 items, n = 55, 7 items, n = 86) and followed Samuels (2017):

1. Dimensions with an eigenvalue > 1 of interest for retention (Kaiser Criteria).
2. Remove dimensions without 3 or more items 'loading' them > 0.4.
3. Remove items: with communalities < 0.2 (none); not loading any dimension > 0.3; which significantly cross-load dimensions (> 75%).
4. Retained Dimensions should account for > 50% of variance in the original data.
5. Dimension Cronbach α = .55 is an ideal minimum for small samples (50-100).

Scree Plots reflect step 1, but iteration through steps 2 & 3 lead to the solution table below.

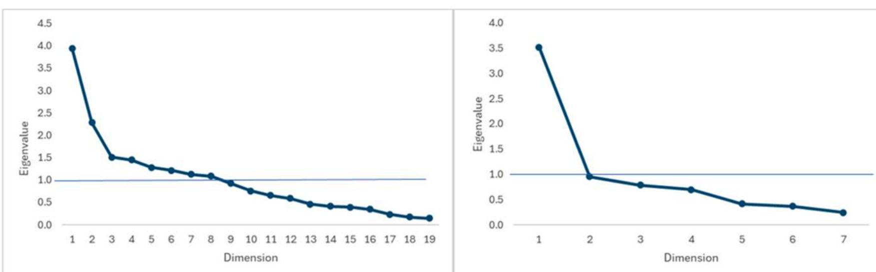

Table A2. CATPCA Overview (Bootstrapping 1000 samples, Bias Corrected and Accelerated 95% confidence intervals, chosen for a small sample with potential skewness).

(a) Component Loadings

CATPCA Partition 1 (N=55)	Non-Bootstrapped (NBS)				Bootstrapped (BS)		
	1	2	3		1	2	
Q12.1					0.581		
Q12.2	0.511						
Q12.3			0.668		0.588		
Q12.4					0.580		
Q13.1	0.821				0.733		
Q13.3			0.719				
Q13.4	0.471				0.394		
Q14	0.764				0.647		
Q15.1					0.587		
Q15.2			0.765		0.401		
Q15.3					0.517		
Q15.4					0.728		
Q15.5						-0.527	
Q16.1		0.757				0.508	
Q16.2		0.700				0.815	
Q16.4		0.694				0.726	
Q16.5		0.578		Total			Total

Notes:

All significant (>75%) crossloading items were removed from the solutions and for clarity all non-signficant (<75%) cross-loadings deleted from all remaining items in this

Parition 1: 3 dimension rotated solution was found in 12 reductive steps. Once the 3 dimension solution was stabilised the analysis was run again in 9 steps aiming to maximise % variance. Boostraped 2 dimension solution was stablised in 9 steps.

Partition 2: 2 dimension rotated solution and bootstrapped single dimension solution were found in 7 steps.

CATPCA Parition 2 (N=86)	NBS			BS
	1	2		1
Q17.1		0.893		0.608
Q17.2		0.693		0.760
Q17.3	0.561			0.578
Q17.4	0.922			0.786
Q17.5	0.892			0.784
Q17.6				0.821
Q17.7		0.672	Total	0.591

(b) Model Summaries

α	0.58	0.55	0.45	0.90	0.80	0.60	0.90
Eigenval.	2.05	1.97	1.60	5.62	3.82	1.24	6.06
% VAF	18.67%	17.92%	14.52%	51.13%	27.27%	15.98%	43.37%
Rotation:		Varimax			N/A		
Norm.:		Kaiser			N/A		

α	0.71	0.65	0.903	0.85
Eigenval.	2.17	1.88	2.160	3.77
% VAF	36.09%	31.34%	67.40%	53.92%
Rotation:	Varimax			N/A
Norm.:	Kaiser			N/A