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The impact of AI Adoption on engineers' Job Satisfaction and Organisational Culture: A Systematic Literature Review and Roadmap for Engineering Education

Mostafa Mohamad[1], Tariq Saali[2], Michael Nii Laryeafio[3], Samuel Ayertey [4], Derick Nyame[5]
[1]College of Interdisciplinary Studies, Zayed University AbuDhabi, UAE (0000-0001-7172-1110)
[2] College of Education, American University in the Emirates, Dubai, UAE. (0000-0002-9890-3341)
[3&4]Arden University,(0000-0003-1257-8398 & 0000-0003-0834-8741)
[5]University of Wolverhampton (0009-0007-7517-9585)
[1]mostafa.mohamad@zu.ac.ae, [2]tariq.saali@aue.ae, [3]m.niilaryeafio@gmail.com, [4]sbayertey@yahoo.com , [5]derick2702@hotmail.com

Abstract— **This systematic review examines the impact of artificial intelligence (AI) adoption on the engineer's well-being, job satisfaction, and the overall organisational culture. Our unconventional review is based on corporate data from leading consultancy firms such as PWC and Mackensy and 200 peer-reviewed articles that address the organisational environment for engineers in major industries such as energy, construction, and telecommunications. While AI enhances operational efficiency and skill development for engineers and supports the organisational culture, it concurrently exacerbates stress, autonomy erosion, and emotional labour in control-oriented environments. Our review pointed out six interconnected dimensions: (1) AI as opportunity versus threat, (2) gigification versus full automation, (3) emotional labour under algorithmic control, (4) human skills' enduring relevance, (5) participatory implementation, and (6) ethical safeguards. These themes were conceptualised based on a mixed framework of Job Demands-Resources (JD-R) and Socio-Technical theories to explain how the workplace culture mediates AI's psychosocial impacts on engineers. Our study presents evidence-based recommendations for human-centric AI integration in areas of co-design protocols, continuous upskilling, and transparent governance structures. This paper contributes to the foregrounding gap on "*how AI reshapes the engineer's well-being and the organisational culture as a whole*". It also has replicable findings for technical jobs that have a similar context to the engineers serving in the energy, construction, and telecommunication industries.**

Keywords— ***Artificial intelligence, Computer Engineering Occupation, Organisational Culture, Job Satisfaction, Socio-Technica Theory, Job Demands-Resources Model, Engineering Education***

JEET Category—**Review**

I. INTRODUCTION

The concept of Artificial Intelligence (AI) has progressed from being a mere dream to becoming an integral part of industries and economies. The discussions are mostly centered around the effects it would have on a whole range of jobs, but there is an irony to it all, and that is the fact that the people who are at the forefront of the revolution they are helping to create are the creators themselves (Brynjolfsson & McAfee, 2023; Mohamad et al., 2025). These skilled and knowledgeable employees not only matter for their satisfaction and well-being but also influence the innovation and competitiveness that technology-driven companies require (Zadow et al., 2023). Therefore, it is crucial to examine the impact of AI adoption on engineers' job satisfaction, a pertinent area of research for both engineering and digital business education.

The importance of the topic is further emphasized by the rapid growth of AI technologies in the engineering process, from AI-based code assistants and automated testing tools to generative design tools and predictive management systems. However, research on this socio-technical phenomenon has been fragmented to date, with currents of knowledge flowing through a broad array of journals on information systems, organizational behaviour, human-computer interaction, and digital innovation. The fragmentation has resulted in difficulties in crafting an overarching understanding of the fundamental issues. As such, an SLR is required to provide a rigorous, replicable, and transparent approach to understanding existing knowledge, integrating disparate findings, and identifying the "big questions yet to be answered." Snyder (2019) encapsulates this requirement for an SLR.

This research answers this call by conducting a bibliometric and thematic SLR of 200 peer-reviewed publications from January 2018 to January 2025 and reports from prominent consulting firms such as PwC and Mackensy. Our review addresses the dominant research clusters and themes, theoretical foundations, and research methods, and provides a guideline for educators and professionals on the positive and dark sides of AI adoption in the computer engineering profession. The results demonstrate the dual effect of AI on job satisfaction, which we term the augmentation-alienation paradox. They also demonstrate the role of organizational culture as a key mediator in the development of the

Mostafa Mohamad
College of Interdisciplinary Studies, Zayed University AbuDhabi, UAE
mostafa.mohamad@zu.ac.ae

phenomenon. Finally, we identify several critical research gaps, most notably a lack of longitudinal studies and research

grounded in non-Western contexts, and we provide a clear roadmap for future scholarly inquiry.

I. The Review Methodology

This study employs a systematic literature review methodology, incorporating both bibliometric and thematic analysis to ensure a comprehensive and rigorous synthesis of the research field (Hansen et.al., 2022). The process followed the well-established PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency and replicability.

A. *Search Strategy and Data Sources*

A systematic search was conducted across four major academic databases known for their comprehensive coverage of the target disciplines: Scopus, Web of Science, ACM Digital Library, and IEEE Xplore. The search was limited to peer-reviewed journal articles, conference papers, and book chapters published between January 1, 2021, and January 31, 2026. The search string was designed to be comprehensive, combining keywords related to the technology, the professional group, and the outcomes of interest:

- (Artificial Intelligence\ OR \AI\OR \Machine Learning\ OR \Generative AI\),
- (Engineer OR \Software Developer\ OR \Technologist\ OR \Data Scientist),
- (Job Satisfaction\OR \Employee Well-being\OR \Work Engagement\OR \Employee Experience\), AND
- (\Organisational Culture\ OR \Organizational Culture\ OR \Workplace Culture\).

B. *Inclusion and Exclusion Criteria*

Table I presents the inclusion and exclusion criteria to help the reader validate the review findings and reinterpret them from a different perspective or discipline.

TABLE I
Inclusion and Exclusion Criteria for the Systematic Review

Criteria	Inclusion Specification	Exclusion Specification
Publication Type	Peer-reviewed journal articles, conference papers, book chapters.	Non-peer-reviewed materials (e.g., editorials, white papers, dissertations, pre-prints).
Language	Published in English.	Publications in any other language.
Timeframe	Published between January 2021 and January 2025.	Published before 2018 or after January 2026.
Core Focus	Must empirically or theoretically address the relationship between AI adoption and the work experience (job satisfaction, well-being) of engineers or similar technical professionals, and/or organisational culture.	Purely technical papers on AI algorithms, studies where engineers are not the primary subjects, or papers focusing solely on AI's impact on firm-level financial performance without addressing employee-level outcomes.
Disciplinary Area	Must originate from or be highly relevant to organisational behaviour, information systems, or digital innovation.	Papers from fields with peripheral relevance (e.g., purely clinical psychology, educational technology outside a workplace context).

C. *Screening Process and Final Sample*

The screening process followed the PRISMA 2020 flow diagram, as illustrated in Figure 1. The initial database search yielded 1,845 records. After removing duplicates, 1,210 unique records were screened based on their titles and abstracts, leading to the exclusion of 995 records that did not meet the core focus criteria. The remaining 215 full-text articles were assessed for eligibility, and a further 15 were excluded for reasons such as being inaccessible, having an inappropriate methodology, or failing to directly address the research questions. This resulted in a final sample of 200 articles for the bibliometric and thematic analysis. This sample constitutes our survey corpus, providing a robust foundation for synthesizing the field's recent developments.

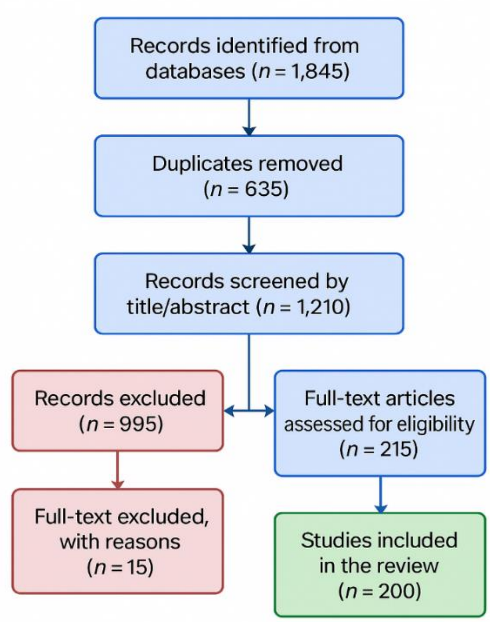

Fig. 1. PRISMA Flow Diagram of the Literature Screening

D. Data Analysis

The strategy used was a two-step strategy. The first was a bibliometric review of the 200 articles using VOSviewer. This examined the publications over time, identified the most productive publications and countries, and also conducted a co-occurrence analysis of author keywords. The second was a thematic synthesis of the qualitative findings in the 200 articles (Kushnir, 2025). This was done by first conducting open coding to develop initial concepts, followed by axial coding to develop more overarching themes on the impact of AI on job satisfaction and culture (Zhao et.al., 2026).

II. REVIEW FINDINGS

A. Bibliometric Analysis of the Research Landscape

The bibliometric analysis of these 200 papers reveals that not only is the domain expanding, but it's also drawing on diverse research traditions. Publication output is increasing, with the number more than doubling in 2021 compared to 2026. The origin of the published works also matters, with the majority coming from the USA, followed by the UK, China, and Germany. The top journals in this domain include Information Systems (MIS Quarterly, Information Systems Research), Engineering Education (Journal of Engineering Education and Transformation), Organizational Behavior (Journal of Applied Psychology, Organization Science), and technology management. The keyword co-occurrence map in Figure 2 reveals three distinct intellectual clusters. Cluster 1 (Blue) includes words such as "*algorithmic management*," "*performance*," "*autonomy*," which reveal a critical view of AI in the workplace. Cluster 2 (Green) includes words such as "*human-AI collaboration*," "*creativity*," "*skill development*," which reveal a more optimistic view of AI in the workplace. Cluster 3 (Red) includes words such as "*organizational culture*," "*change management*," "*leadership*," which reveal the role of the organization in mediating the impact of AI in the workplace. The significant links between these clusters reveal the socio-technical nature of this phenomenon.

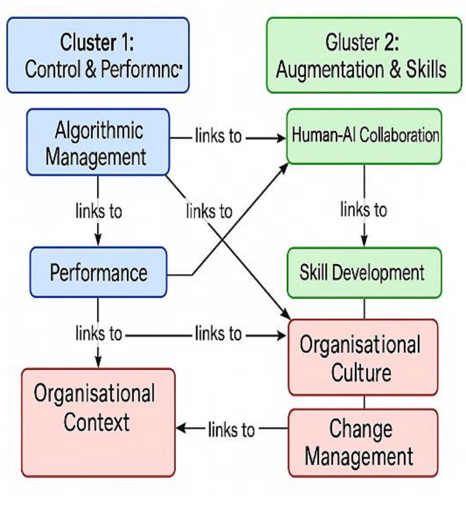

Fig. 2. Keyword Co-occurrence Network Clusters

B. Thematic Findings: The Duality of AI's Impact on Engineers' Job Satisfaction

Our investigation of the 200 articles reveals a two-sided, crystal-clear image of the role of AI in affecting job satisfaction among engineers. The augmentation-alienation paradox is a phenomenon that reveals the double impact of AI on professionals.

1) The Augmentation Effect: AI as a Tool for Empowerment and Creativity

The most dominant trend in the literature is that AI increases the capabilities of engineers, which in turn increases job satisfaction. This occurs mostly through the automation of boring and repetitive tasks. An example can be found in a study on software developers, which revealed that AI-based automated testing and documentation tools for codes "*liberate engineers from tedious grunt work, allowing them to focus on more complex, creative, and strategically important problem-solving*" (Mason & Kuttal, 2025, p. 112). In addition to automation, AI can be considered a collaborative partner for engineers. GitHub Copilot and other AI-based automated coding tools can be considered "*symbiotic partners in the creative process*," leading to a state of flow for engineers, making them feel extremely satisfied and creative (Geroimenko, 2025; Mohamad et al., 2026). The opportunity to collaborate and develop the latest AI technology can also be a source of motivation for many engineers, making them more marketable and increasing their skill set (Hutson & Ceballos, 2023).

It has the potential to assist people in learning new skills as well as to enhance their performance at work through the completion of tasks in a faster and more efficient manner. In turn, this can make most people feel content with their work. It can take over the dull and mundane tasks, leaving people to concentrate on the most important and challenging tasks. For instance, when virtual assistants take over dull customer care tasks, people have more time to concentrate on more interesting and significant issues. With a little reorganization, people can feel more accomplished while having far fewer dull moments at work. In addition to that, people can also be encouraged to interact with modern technology, thereby assisting in the development of skills.

Research carried out in 2018 by Brougham and Haar revealed that employees in firms that utilized AI were more likely to take part in training and reskilling, thereby enhancing their career prospects as well as their job satisfaction. In the health sector as well as finance, there have been positive correlations with increased precision in diagnosis as well as a reduction in errors, thereby creating trust in one's professional work (Raisch & Krakowski, 2021).

2) The Alienation Effect: AI as a Source of Pressure and De-skilling

On the other hand, a counter-narrative of alienation and pressure also emerges in the literature. Perhaps the most prominent of these is the rise of algorithmic management. AI technologies that monitor productivity and track employees' keystrokes and task assignments have the potential to lead to a severe loss of autonomy, which is a major determinant of job satisfaction (Kyriakou & Otterbacher, 2023). This has been described by engineers who feel "micromanaged by an algorithm," which leads to a lack of trust and a culture of surveillance.

Another major concern is the fear of de-skilling and the loss of skills due to AI. While AI has the potential to automate some of the tasks, there is also the threat of the devaluation of engineering skills in the future. For example, the over-reliance of AI code assistants has the potential to lead to a devaluation of the most fundamental engineering skills, such as problem-solving and critical thinking, among junior engineers (Eldebeky et.al., 2025). This creates a stressful environment where the engineer feels they have to be in a constant race to keep their skills relevant in the face of smarter machines. In FinTech and blockchain engineering, Hamed et.al (2025) emphasize the competitive environment, where developers' solutions are compared to those free platforms generated via ChainGPT, Workik, and Alchemy.

Further, AI could limit workers' independence, which would reduce their satisfaction with work. The increased supervision would affect interpersonal relationships negatively. For instance, with productivity being constantly monitored through AI analytics, there would be a lack of trust. For example, Kellogg et al. (2020) found that algorithmic management of ride-sharing services made the workers feel less autonomous, hence less satisfied with their jobs.

Another ethical issue to consider with AI in the computer engineering workplace is depersonalisation. In situations that require direct interaction with customers, AI can take some of the human touch out of the equation. This can negatively impact workers' emotional engagement with their work. According to a CIPD survey done in 2023, 47% of workers in the service sector felt that AI had negatively impacted their interaction with colleagues.

Lastly, it is possible that the sheer intricacy of the AI systems that software engineers work on is a genuine stressor. The fact that it requires a high mental workload to design, debug, and stay current with "black box" machine learning models is a potential source of burnout and exasperation (Avik et.al., 2024). And then there is the moral stress of dealing with the ethics of AI that they are developing.

3) The empirical Tension and Conflicting Results

There are numerous disputes seen in empirical studies on artificial intelligence and work satisfaction. On the one hand, studies show that tools for AI-enabled collaboration and decision-making increase output and pleasure (Raisch & Krakowski, 2021). Moreover, various surveys and case studies show that morale falls when artificial intelligence is seen as intrusive or degrading (Brougham & Haar, 2018; Kellogg et al., 2020).

This divergence may be attributed to a number of factors, including sectoral, cultural, and organizational factors, among others. For example, the perception of artificial intelligence may differ between customer service employees and finance experts. Other factors may include the level of staff involvement in the deployment of AI, the level of openness in the organization, and the organizational culture, among others. The CIPD (2023) noted that companies using participatory strategies in the deployment of AI report high job satisfaction.

On the other hand, although AI may contribute to increased job satisfaction through increased productivity and growth prospects, the satisfaction may not be absolute. This is because the same AI may also contribute to increased job dissatisfaction if not deployed properly and if it does not reflect the organizational culture and the level of control and freedom that employees want to feel in the organization.

4) The Mediating Role of Organisational Culture

One thing is for certain from the review: the impact of AI on the way people feel about their job is not set in stone. It is heavily dependent on the culture inside the company. Two cultural elements stand out from the body of research as being important for a positive outcome.

The first is a culture of constant learning and security, where AI is seen as a threat. In this case, engineers feel positive in an environment that encourages experimentation and learning from mistakes (Jayshree & Edmondson, 2026). This allows them to express their worries about AI without fear of retaliation, which is important for their well-being. The second is a data-driven but human-centred culture. AI can help organizations make more data-driven decisions, but it is organizations that use AI to support decision-making rather than lead it that have the highest levels of autonomy and job satisfaction among engineers (Mohamad et al., 2025b). This is important for the leadership to champion.

The definition of workplace culture is multidimensional and includes a complex bundle of associated factors. For example, *think of support* (how much room people have to define their own work), *communication* (how open and unambiguous communication is), and *justice* (how people perceive the fairness of their opportunities and treatment). But when AI is added to the mix, these factors influence people's perceptions of AI in different ways. People who have a lot of autonomy in their work tend to view AI as a positive force to help them make decisions, not a negative force threatening their employment. As West and colleagues (2019) note, "*powerful signals of justice and support help to protect people from the jitters of being surprised by technology*." On the other hand, people who experience poor communication and collaboration may feel apprehensive (like they are being monitored, feel insecure about their employment, and wonder what the implications of AI mean for their future).

Our review also pointed out that culture has also been considered as a "*buffer*" or "*amplifier*" of AI Impacts. The impact of culture on the interface of AI and our happiness is a double-edged sword that can bring us up or bring us down. As long as people feel included, supported, and secure, AI is more like a supportive sidekick that aids the workflow but does not control it. This makes us less likely to be unhappy in our jobs or stressed by technology (Liu et al., 2023). However, in a culture that emphasizes control, overwork, and backroom decision-making, the effects of AI can be amplified for the worse. As technology increasingly monitors, directs, and takes over our activities with little or no human input, people feel trapped, voiceless, inhuman, and more stressed by the technology meant to help us (Thorpe et al., 2025). This is particularly important for the UK's service sector, which is embarking on exciting AI initiatives to monitor performance, generate adaptive work schedules, and get to know consumer preferences and needs.

C. Theorization and Conceptualisation: An Interdisciplinary Perspective

This part of our review explores the most common theories and models in the literature to understand how AI influences the happiness, empowerment, and job satisfaction of computer engineers. Six theories/models are critically reviewed, and a detailed table is presented to compare and contrast them in terms of their relevance to answering the research question. Table 2 presents this detailed comparison and the implications for the computer engineering educators who would investigate the dual effect of AI on the profession.

1. Job Demands-Resources (JD-R) Model

Radic and colleagues created this model and termed it the JD-R Model (Radic et al., 2025). The model proposed that while there are certain needs that must be fulfilled in a job, such as time constraints and the quantity of work to be performed, having more freedom, support, and feedback is highly desirable. All of this could collectively impact an employee's happiness, quality of life, and levels of tiredness. It is more likely that we would feel overwhelmed and unhappy when there is more to be done than we can accomplish (Ashoer et al., 2025). According to this approach, artificial intelligence technologies are contradictory as it is likely that AI could be both a source of work and a source of work to be performed. This can also help in relieving mental and physical stress through better accuracy in decision-making processes and providing real-time insights (Liu et al., 2023). For example, AI can relieve the management's stress through more efficient management of the scheduling of shifts with the help of predictive scheduling, which can reduce errors (Qadir et.al., 2026). AI chatbots could reduce the workload associated with routine customer interactions, allowing employees to focus on more important tasks and hence increase job satisfaction and task variety (Henkens et al., 2025).

As we stand here today, AI is at a crossroads (both as a possibility and a necessity). AI technology holds potential for reducing mental and physical strain by reducing tedious work, improving decision-making precision, and providing timely information (Liu et al., 2023). Consider a predictive scheduling technology (for example, it promises to reduce some planning burdens for managers, reduce stress levels, and prevent human error) (Qadir et.al., 2026). At the same time, AI may reduce the workload experienced by service staff by dealing with mundane client engagements, thereby enabling employees to engage in more meaningful activities and possibly increasing satisfaction and variety in the work being done (Henkens et al., 2025). However, artificial intelligence systems may also make work more difficult. Artificial intelligence systems used for surveillance, for example, require constant monitoring, which may cause stress levels to rise (Thorpe et al., 2025). Technostress, which refers to the difficulties faced by people who need to adapt to artificial intelligence systems of a complex nature, may also arise (Routray et al., 2025). AI systems used for performance appraisals that often overlook the human components of performance may exacerbate technostress in service settings (Li et al., 2025).

Moreover, the use of AI-based scheduling systems has also highlighted problems of temporal uncertainty. For instance, several shopworkers in the UK faced burnout after an AI system, which gives efficiency the first priority over work-life balance, changed their patterns of shifts (Upeksha et al., 2025). These examples provide an idea of how artificial intelligence can subvert control, which is one of the fundamental predictors of well-being, as per the JD-R model. However, the JD-R model has vividly described the dualistic potential of artificial intelligence, which influences psychological outcomes. For instance, in service professions that require high emotional labor, firms that use artificial intelligence without providing more work resources, including emotional support, run the risk of witnessing employee discontent and burnout.

2) Socio-Technical Theory (STS)

According to contemporary STS theory, this is because we should not see AI as a singular breakthrough but rather as part of a system that is co-optimized with other components. STS theory, by shifting our attention away from flashy algorithms and towards the ecosystems that these algorithms inhabit, also helps us understand how these same capabilities, depending on how they are deployed, might improve or decrease engineers' happiness levels and satisfaction with their jobs (Kudina & van de Poel, 2024). When it comes to happiness levels and satisfaction with one's job, ergonomics research also supports STS theory, which argues that improvements will be seen if an AI system is deployed at a system level that still allows for human discretion, feedback, and transparent coordination (Koster et al., 2022). According to ergonomics theory, human-AI systems that are designed with a distributed, joint cognitive perspective will be better at supporting complex collaborative activities, positive moods, and learning, compared with a simple one-on-one "humans vs. machines" perspective on things (Naikar et al., 2023; Liu et al., 2023).

STS also offers insights into the risks of empowerment that are linked to algorithmic management. Research using large-scale data from European organizations has revealed that data-based decision-making can lead to reduced job autonomy and rewards, which can negatively affect workplace well-being if not addressed (Kinowska & Sienkiewicz, 2022). In other words, the efficiency of AI can only improve satisfaction if the organization's levers are aligned and adjusted accordingly (Oliveira et al., 2025).

One of the main STS-based remedies is participatory design. Current studies on human-computer interaction have revealed that the involvement of engineers in the design of the rules of algorithms, explanations of algorithms, and scheduling can transform the use of AI from surveillance to empowerment tools that can improve perceptions of fairness and well-being (Zhang et al., 2022). Systematic reviews of AI-based participatory design indicate that the benefits include accessibility and collaboration; however, there are also concerns that include bias and cognitive overload (van den Broek et al., 2024).

Lastly, STS recasts the notion of culture as infrastructure. By integrating humanistic sociotechnical principles into AI systems, such as clear oversight, level of explainability commensurate with the task, and coordination at the team level, there is a better chance of seeing a thriving engineering group that is empowered than if we pursue model performance (Kudina & van de Poel, 2024; Naikar et al., 2023). Thus, STS offers a way of grasping the dual nature of AI: the happiness, empowerment, and satisfaction of computer engineers depends on the co-design of technical capability and how the organization is structured, who has the authority, and how the organization is participatorily governed.

3) The Theory of Self-Determination (SDT)

According to Self-Determination Theory (SDT), well-being at work increases when these fundamental human needs are satisfied: autonomy (perceived choices), competence (perceived mastery), and relatedness (genuine connection with others). Recent studies suggest that these needs increase motivation, vitality, and positive work attitudes in various occupations (Ryan & Deci, 2022). From the SDT perspective, various AI engineering tools that increase mastery will increase happiness and satisfaction at work as long as they provide genuine control over procedures and speed. If well-integrated into the workflow and appropriate to the task, AI will increase feelings of control and mastery because it becomes part of the workflow and not an inhibitor of it (Naikar et al., 2023; Zhang et al., 2022).

SDT argues that things can, however, go awry if we lose our independence or relatedness at work because of AI. Large samples from European countries have found that algorithmic management can undermine our level of independence at work, including our satisfaction with rewards, leading to a quiet undermining of our happiness at work. For instance, satisfaction can drop if power to decide is handed over to an algorithm (Kinowska & Sienkiewicz, 2022).

In human-computer interaction research, workers, including engineers, have been found to be in a much better state if they have a say in how the rules or explanations that guide AI systems are developed, co-designing or co-configuring, because it is much more related to their independence or fairness, compared to systems where AI is merely “slapped in” without their say (Zhang et al., 2022).

The SDT can also help understand relatedness at the team level in human-computer interaction research. Designing human-AI systems with shared, distributed thinking can enhance team functioning, including relatedness, leading to greater happiness because it can enhance team coordination, safety, belonging, and related to that, relatedness can enhance positive moods or satisfaction in the complex world of engineering. However, if AI systems mediate interactions with strict metrics or surveillance, they can undermine relatedness, leading to lower happiness, even if performance is enhanced (Kinowska & Sienkiewicz, 2022).

For Self-Determination Theory to be applied to the implementation of AI in organizations, it is necessary to: first, establish configurations that support autonomy, including offering real choices to computer engineers in their approach, settings, and override options; second, foster competence, including offering transparent feedback and opportunities to develop skills; and third, foster relatedness, including promoting collaborative practices in governance structures. These practices link the implementation of AI with psychological factors that enhance computer engineers’ happiness, empowerment, and satisfaction with their work (Ryan & Deci, 2022; Zhang et al., 2022).

4) Conservation of Resources (COR) theory

The Conservation of Resources (COR) model provides an understanding of why this is all happening by viewing engineers as people who pursue resources. We pursue things like time, energy, skill, independence, and self-esteem. When these resources elude us or when we think they might, we experience stress and misery. The advantages of AI are quite practical: time saved, cognitive ease of mind, and an improvement in our professional competence. These are all gains in resources. These resource gains are linked to higher happiness and a greater sense of empowerment. Conversely, things such as algorithmic management, increasing surveillance, decision space reduction, or increasing our goals without rewards are losses of resources. These are losses of autonomy, control, and fairness. These losses are linked to lower happiness and lower job satisfaction (Kinowska & Sienkiewicz, 2022).

The COR model also provides an understanding of loss spirals. Loss spirals are where we are worried about becoming obsolete or losing competence. This causes us to work longer hours to try to maintain our skills. If we don’t receive gains such as having more free time to learn new skills, rewards, and career advancement, then we experience further losses. Research has shown that algorithmic management causes burnout and threat. This has a negative effect on our well-being unless we have a high person-job fit and a well-designed process (Zayid et al., 2024).

In conclusion, we can now understand why algorithmic management with AI has a positive effect on happiness and satisfaction with our jobs as computer engineers when we gain resources. Conversely, it has a negative effect on our happiness and satisfaction with our jobs when we lose resources. Therefore, to implement algorithmic management with AI well in our workplaces, we must create resource buffers.

5) Person–Environment (P–E) fit theory

According to the Person-Environment (P-E) fit theory, people experience high levels of happiness with regard to their work when what they are able to do and what they are interested in match what the work requires in relation to the organization. Current research has remained consistent with the notion that fit entails ability-demand fit; it also includes needs-supply fit. Moreover, it predicts satisfaction, commitment, and well-being in various contexts (Pasca, 2022). When an AI enhances an engineer’s ability to explore more quickly and diagnose more deeply, while also reflecting an engineer’s values with regard to experimentation and craftsmanship, it enhances ability-demand fit and needs-supply fit. This enhances happiness and satisfaction with one's work. Conversely, when an algorithmic workflow does not match with an individual's professional identity or with one's desired workflow, it can enhance feelings of misfit, which negatively influences satisfaction and psychological empowerment (Pasca, 2022).

TABLE II
THEORIES/MODELS FOR CONCEPTUALISING THE DUAL IMPACT OF AI ON THE COMPUTER ENGINEERS' SATISFACTION

Model / Theory	**Core lens for AI & work**	**Positive AI pathways (satisfaction & empowerment)**	**Negative AI pathways (satisfaction & empowerment)**	**Common indicators / measures**	**Key References**
Job Demands–Resources (JD-R)	Balance of job demands (e.g., workload, cognitive load) and resources (e.g., autonomy, feedback). AI can function as either.	When AI reduces repetitive load and is paired with autonomy/support, well-being and engagement rise; resource gains improve satisfaction and empowerment.	AI that raises pace/surveillance without added resources increases strain/burnout; well-being and satisfaction fall.	Burnout/engagement scales; perceived demands/resources; affective well-being.	Kinowska & Sienkiewicz, 2022; Zayid et al., 2024
Socio-Technical Systems (STS)	Outcomes depend on joint optimisation of social structures (roles, culture, governance) and technical subsystems (AI tools, workflows).	Participatory co-design, role-appropriate explainability, and team coordination frame AI as a mastery resource, increasing satisfaction and empowerment.	Top-down algorithmic control and opaque deployment reconfigure power/communication, risking alienation and lower commitment.	STS design principles; participatory design artefacts; team coordination assessments.	Kudina & van de Poel, 2024; Naikar et al., 2023; McKay et al., 2020
Self-Determination Theory (SDT)	Need satisfaction for autonomy, competence, and relatedness predicts motivation and well-being in AI-mediated work.	AI that scaffolds competence (diagnostics/code assist) and preserves discretion/relatedness increases happiness, empowerment, and job satisfaction.	Prescriptive or opaque AI that removes discretion or crowds out collegial exchange thwarts needs and depresses satisfaction.	Basic Psychological Need Satisfaction; intrinsic motivation; autonomy/relatedness indices.	Ryan & Deci, 2022; Kinowska & Sienkiewicz, 2022
Conservation of Resources (COR)	People strive to acquire/protect resources (time, energy, skills, status); stress and dissatisfaction follow resource loss or credible threat.	AI yielding time savings/skill growth creates resource gains and can enhance well-being and empowerment.	Algorithmic practices that erode autonomy/rewards or heighten obsolescence fears trigger loss spirals → burnout and reduced empowerment.	Resource appraisals; burnout/engagement; perceived threat.	Zayid et al., 2024
Person–Environment (P–E) Fit	Satisfaction/empowerment hinge on ability–demand and need–supply fit between engineer and AI-shaped job context.	AI that expands problem space and aligns with values for experimentation/craftsmanship strengthens fit and satisfaction.	Misfit when algorithmic workflows conflict with identity or constrain preferred practices reduces satisfaction/empowerment.	Polynomial regression/surface tests for fit; value congruence; autonomy measures.	Pasca, 2022; Kinowska & Sienkiewicz, 2022
Job Demand–Control (JD-C)	High demands harm well-being mainly when decision latitude is low; high control can turn demands into growth.	Configurable AI with human override/tool choice raises decision latitude so higher scope/pace become learning opportunities → greater satisfaction and empowerment.	Tightly scripted, opaque AI with monitoring and little say places work in high-demand/low-control → strain and lower satisfaction.	Job Content Questionnaire (demands, control, support); strain/affect indices.	Naikar et al., 2023; Kinowska & Sienkiewicz, 2022

Research on AI-enabled management pactices has found that how people feel at work depends on two big things: how well their autonomy is maintained by AI, and how well their rewards are maintained in relation to what AI is doing. A Europe-wide study of practices found that algorithmic management indirectly affected workers' well-being negatively by chipping away at their autonomy and rewards, consistent with the view that fit between people and their work is revealed in negative outcomes (Kinowska & Sienkiewicz, 2022). More recent modeling research found that how well people fit their work can help mitigate burnout and feelings of threat associated with algorithmic management, thus sustaining satisfaction and empowerment even in an AI-managed workplace (Zayid et al., 2024). Finally, research on human-computer interaction found that working with an AI partner is more meaningful—and thus more satisfying—when there is a good fit between how tasks are distributed and workers' expectations of collegial roles, another look at fit between values and practices (Sadeghian, 2022).

The takeaway is that to use AI to enhance happiness and empowerment among engineers, organizations should co-create with their engineers to create an AI that maximizes fit between what the AI can do well and what their skills are, what their rewards are, and how they can contribute with AI to organizational goals (Pasca, 2022; Kinowska & Sienkiewicz, 2022; Zayid et al., 2024).

6) Job Demand-Control (JD-C) model of work design

According to the Job Demand-Control (JD-C) model's basic claim, "*When demands increase, things go bad if you have little room to decide, but can go better if you have plenty of room to control things*." In the case of AI-assisted engineering, tools with high demand pressures but also high control options tend to lead to higher happiness, psychological empowerment, and work satisfaction. New research on systems design suggests human-AI combinations with high adjustability of autonomy, an appropriate level of explanations according to user roles, and team-level human-AI coordination to maintain high control in complex contexts, which are positively related to better mood and better learning outcomes (Naikar et al., 2023). Conversely, a study on algorithmic management across all of Europe also suggests it can erode autonomy and reward structures, indirectly negatively influencing well-being at work (an effect consistent with the high demand-low control part of JD-C) (Kinowska & Sienkiewicz, 2022).

A further line of research suggests that algorithmic management leads to higher burnout and threat perceptions, whereas contextual factors such as good fit and process design can mitigate these negative outcomes, which are practically useful to increase control to offset high demand pressures on well-being (Zayid et al., 2024). Lastly, a sociotechnical approach to human-AI systems reminds us that "control" in human-AI systems is not just a feature of user interfaces; it's also a feature of the system itself. Thus, we must also consider human roles, human rewards structures, and human decision processes to match user discretion with human-AI system capabilities to achieve desired outcomes (Kudina & van de Poel, 2024). In conclusion, when you introduce an AI system into an organization, don't forget to match high demand pressures with high decision latitude.

III. Research Gaps and Future Recommendations

The evidence based on AI, employee well-being, and workplace culture is expanding, albeit in a fragmented fashion. Much of the research has been conducted in isolation; well-being studies rarely consider the technology-related aspects of stress and well-being, and AI-related studies of the workplace have concentrated on productivity, not employee well-being. (Sadeghi, 2024) This lack of integration does not help to clarify the complex interplay of algorithmic technology and human and cultural factors in the workplace. (Brougham & Haar, 2018; Schein, 2010) Most studies have a global or US-centric focus, although the UK service-based economy has a relatively low profile, despite its distinctive approach to regulation and compliance. (Kaaria, 2023) UK-based studies have highlighted the influence of institutional logics and legitimacy pressures on organisational practices. (Burdon & Sorour, 2020) Other studies, conducted in the context of other non-Western economies, such as the fintech industry in Ghana, have highlighted the impact of different institutional arrangements on the research approach and findings. (Gozman et al., 2022). As shown in Figure 3, we identify six research gaps that future studies may address.

The first gap relates to the lack of longitudinal studies. Most studies provide a cross-sectional view of the situation but do not follow the dynamics of satisfaction, skills, identity, and cultural sense-making over time as AI moves from pilot to implementation. (Cummings-Koether et al., 2025) This calls for studies that follow cohorts through different phases of the implementation, combining repeated surveys with experience sampling and follow-up studies. Where possible, studies could also draw on usage statistics and human resource outcomes. This would be more in tune with culture-in-action perspectives, which stress the dynamics of organisational assumptions over time. (Schein, 2010).

A second gap relates to the lack of diversity in the context of studies. Most studies of AI and culture in the UK context focus on software engineers working in large technology firms, with little exploration of other fields of engineering or of customer-facing services. (Montes et al., 2025) This calls for more comparative studies of civil, mechanical, and biomedical engineers, as well as start-ups, government agencies, and non-technology services. UK-based studies could draw on established links between compliance cultures and organisational change. (Burdon & Sorour, 2020; Gozman et al., 2022).

A third gap that exists in the literature relates to the role that leadership plays in mediating the human-AI relationship. Though leadership is sometimes acknowledged, there is a lack of understanding regarding the role that leadership plays in influencing the human-AI relationship, particularly in relation to factors such as sense-giving in relation to model updates and the provision of ethical guidance to human engineers (Zárate-Torres et.al., 2025) Following on from the culture theory that posits leadership as a key architect of cultural assumptions, future research needs to be conducted to determine whether there exists a causal link between leadership styles and human AI collaboration, and whether training interventions can be effective in influencing manager and human AI.

A fourth gap that exists in the literature relates to the absence of attention to team-level factors, with most research being conducted on individual engineers, despite the fact that AI-enabled work is a team-based activity. (Arslan et al., 2021, pp. 75-88) Future research needs to be conducted to determine how collaboration and social cohesion change with AI, and how new hybrid roles such as human-AI coordinators emerge and gain legitimacy. This can be done by drawing on cultural analyses that examine the link between group routines and human AI collaboration, and that recognize the importance of multi-method approaches that include social network analysis and ethnography (Schein, 2010).

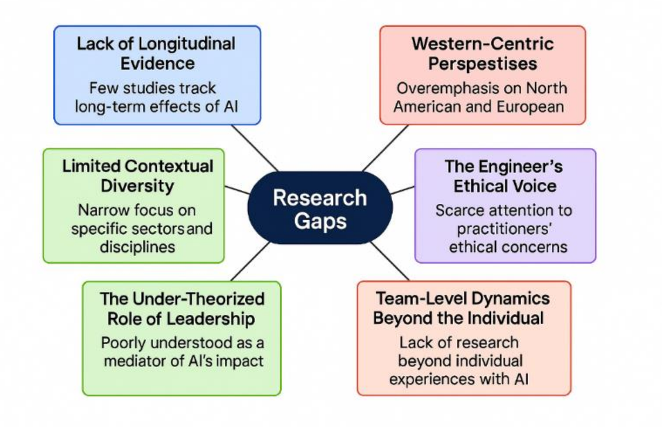

Fig. 3. Research Gap

The fifth gap relates to Western-centric thinking. Most of the literature has been written by people from North America and Europe, and therefore we have not gained insight into the influence of cultural values, different work practices, and regional legislation in other parts of the world (Rode et.al., 2022) Research in this area should focus on comparative studies in the Global South, co-created research with colleagues in the Global South, and UK-based research to explore the impact of oversight cultures on the effects of AI. This suggestion is supported by research on compliance and legitimacy in UK services (Burdon & Sorour, 2020) as well as research in non-Western settings that have demonstrated different paths of development (Gozman et al., 2022).

The last gap that was noted was that there were no studies done on the ethical voice of engineers. While there was a lot of debate on the subject of ethics at work, there is very little research on how engineers perceive and deal with ethical dilemmas in their line of duty. How these moral activities impacted job satisfaction was also not well researched (Wooten, 2001). Research in this area should draw on research that demonstrated the relationship between technological awareness and positive attitudes in employees. It should also draw on cultural research that views value conflicts as opportunities for re-socialisation. Research using critical incident techniques to explore escalation routes as well as diary studies to explore the relationship with retention and product quality would also be useful in this area. (Brougham & Haar, 2018; Schein, 2010).

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