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Adapting to AI-mediated workplaces: how STEM trainees navigate new challenges and opportunities

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Abstract

Purpose – The integration of artificial intelligence in workplaces is rapidly transforming employment structures, skill requirements, and decision-making processes. This study examines how AI-mediated workplaces (AI-MWP) impact STEM trainees entering the workforce. Specifically, it explores their preparedness, the challenges and opportunities presented by AI-MWP, and the role of socio-digital skills in shaping their career trajectories.

Design/methodology/approach – This study employs a socio-technical systems (STS) approach to analyze the experiences of science, technology, engineering and mathematics (STEM) interns. Using qualitative research methods, including interviews and case studies, we investigate how AI-MWP influence information sharing, task allocation, workplace interactions and the professional development of recent graduates.

Findings – The findings highlight that AI-MWP introduce new challenges for STEM trainees, particularly in navigating socio-digital skills, workplace autonomy and task ownership. AI-mediated communication reduces informal learning opportunities, impacting trainees' ability to develop professional networks and contextual understanding. Revealing a growing gap in employability frameworks that fail to address the evolving socio-technical demands of modern work, the study also underscores the necessity of digital fluency, adaptability and interdisciplinary collaboration as essential competencies for thriving in AI-MWP.

Originality/value – This study extends STS thinking into the AI-mediated work domain, offering new insights into how digital transformation reshapes employment dynamics. By identifying socio-digital skills as a critical yet overlooked component, we provide actionable recommendations for STEM educators and employers to improve training strategies and bridge the gap between academic preparation and AI-MWP.

Keywords AI-Mediated workplaces, Socio-digital skills, STEM interns, Employment dynamics, Workforce integration

Paper type Research article

1. Introduction

The integration of artificial intelligence (AI), particularly generative AI (GenAI), is rapidly reshaping work environments, altering job structures, skill expectations, and professional relationships (Benbya *et al.*, 2024; Engström *et al.*, 2024). As AI becomes a foundational element across sectors (e.g. from automation and decision support to communication and collaboration) the ability to work effectively alongside AI systems has become a defining feature of employability. Yet, this transformation presents both opportunities and challenges that remain insufficiently understood, particularly for those just entering the workforce. While existing research has examined AI's impact on mid-career professionals and general workforce trends, much less is known about how early-career individuals experience and

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adapt to AI-mediated workplaces (AI-MWP) (Passalacqua *et al.*, 2024; Simón *et al.*, 2024) which are characterized not merely by the presence of AI tools, but by the integration of AI systems into the core logic and operation of organizational tasks and roles (Nguyen and Elbanna, 2025; Babashahi *et al.*, 2024).

This study focuses on STEM trainees who represent a critical yet underexplored population navigating AI-MWP yet are frequently viewed as "future-ready" due to their technical expertise and problem-solving abilities (White and Smith, 2022; Drewery *et al.*, 2023). However, research has shown that such assumptions may oversimplify the realities of digital transformation, which demands more than technical fluency (Ng *et al.*, 2024; Flathmann *et al.*, 2024). Socio-digital competencies, such as the ability to interpret AI outputs, adapt to algorithmically mediated workflows, and collaborate across disciplinary and human-machine boundaries, are emerging as essential (Hughes and Davis, 2024; Chaturvedi *et al.*, 2025). These competencies are particularly important in early-career roles, where employees often lack contextual awareness, informal networks, and institutional knowledge to navigate evolving work practices effectively.

Despite some attention to trainees' roles in digital contexts (e.g. Jackson, 2021; Akour and Alenezi, 2022), few studies have systematically investigated how AI alters the social and technical dimensions of entry-level work. As new graduates come face to face with AI-mediated communication (interactions filtered, facilitated, or shaped by AI tools such as chatbots, recommendation systems, or automated messaging platforms), decision-making, and performance assessment tools (Poon *et al.*, 2024), they are not only expected to get the hang of these technologies but also to read between the lines (e.g. grasping how such systems form team dynamics and organizational expectations). As a result, their learning, visibility, and perceived competence increasingly hinge on such platforms that prioritize speed and structure, often pushing aside informal mentoring, spontaneous exchanges, and subtle social cues (Hughes and Davis, 2024; Ng *et al.*, 2024).

To explore these overlooked dynamics, we turn to STEM contexts, where AI's influence on data-driven and technical work is especially pronounced. This vantage point directs us to interrogate a persistent tension: the assumption that technical know-how alone ensures workplace success (Poon *et al.*, 2024) versus the lived experiences of young professionals grappling with AI-mediated workflows (Simkute *et al.*, 2024), communication challenges (Hughes and Davis, 2024), and shifting expectations (Chaturvedi *et al.*, 2025). Taken together, these themes highlight a significant gap in our understanding of how early-career professionals experience AI-MWP as the assumptions of "future readiness" among STEM graduates obscure the nuanced socio-digital skills, role clarity, and adaptive capacities actually required to thrive in such contexts. This gap points directly to the need for empirical inquiry into both the lived experiences of trainees entering roles where they interact and collaborate with AI and the developmental supports they require to succeed. Accordingly, we ask:

(1) How and why does AI-mediated work experience impact STEM trainees newly entering the workforce?

(2) What are the development and training needs of STEM graduates entering the workforce in AI-MWP**?**

By tackling these questions, our study makes three key contributions. First, we extend STS theory into AI-MWP by examining how AI shapes task design, communication, and identity formation during early career stages. Second, we highlight socio-digital skills as a missing yet vital component of employability, offering a revised competency framework suited to algorithmically mediated workplaces. Third, we generate practical insights for educators and employers seeking to align training programs and workplace practices with the evolving nature of work. By centering the voices of new graduates, we contribute both conceptually and empirically to debates on AI, workforce readiness, and the design of equitable professional ecosystems.

2. Socio-technical systems theory

Socio-technical systems (STS) theory, originally proposed by Trist and Bamforth (1951) at the Tavistock Institute, offers a foundational framework for understanding how organizations function as an interdependent union of two subsystems: the *technical* which comprises tools, technologies, and formal work processes, and the *social* which includes people's knowledge, values, relationships, and organizational structures (Cherns, 1987; Clegg, 2000). The central premise is that optimal organizational performance and worker well-being are achieved not by focusing on either subsystem in isolation, but through the joint optimization of both (Trist and Bamforth, 1951; Mumford, 2006). Over the decades, this theory has evolved to address new organizational challenges, including digital transformation (Ngowi and Mvungi, 2018), remote/smart work (Bednar and Welch, 2020), and now AI augmentation (Ghobakhloo *et al*., 2023; Le Blanc *et al*., 2024). STS research today increasingly explores how automation, algorithms, and AI platforms restructure decision-making, learning, collaboration, and autonomy in complex digital work environments (Thomas, 2024; Yu *et al*., 2023).

Within this framework, several key principles guide effective organizational design: (1) task completeness and meaningfulness, (2) autonomy and control over one's work, (3) the presence of feedback loops to enable learning, and (4) the development of a shared identity or "place in the system" (Cherns, 1987; Appelbaum, 1997; Ngowi and Mvungi, 2018). This theoretical lens is highly relevant to the present study, as AI does not simply "add" to work systems, but it reconfigures both the technical operations and the social fabric of early-career professional experiences. In particular, AI technologies such as automated performance scoring, algorithmic task assignment, and virtual collaboration tools restructure how work is allocated (Bednar and Welch, 2020; Boussioux *et al*., 2024), how trainees interact with peers and supervisors (Hughes and Davis, 2024), and how they interpret their place within organizations (Thomas, 2024). These AI-induced changes do not occur in a vacuum; they interact dynamically with organizational hierarchies, feedback structures, social norms, and training ecosystems (Le Blanc *et al*., 2024; Ghobakhloo *et al*., 2023). STS theory can therefore help us make sense of these interactions, providing an integrated view of how AI reshapes the socio-technical environment in which STEM trainees must adapt, learn, and demonstrate competence.

By applying this framework, our study moves beyond a surface-level examination of technology uptake or user attitudes. Instead, it explores how technical innovations (e.g. AI platforms) and social elements (e.g. mentoring, informal learning, and role clarity) co-evolve in AI-MWP. This theoretical perspective guides our investigation into how the lived experiences of STEM trainees are shaped not just by their individual readiness, but by the broader systemic (mis)alignments and shifts introduced by AI-enabled socio-technical change.

3. AI's impact on work and STEM roles

The integration of AI technologies into workplaces has dual potential: AI can either enhance or diminish job quality. Some studies emphasize AI's potential to enhance productivity, reduce cognitive load, and create new job opportunities (Nazareno and Schiff, 2021; Simkute *et al*., 2024). Others caution against deskilling, job displacement, and the erosion of human expertise in AI-assisted environments (Aiello, 2024; Yu *et al*., 2023). Böhmer and Schinnenburg (2023) describe this phenomenon as the "intellectual impoverishment of work," where AI takes over routine or cognitive tasks, leaving behind roles that are either highly specialized or fragmented and lower in skill. This is especially evident in STEM professions, where automation is rapidly altering the cognitive and technical demands placed on workers (Huang and Rust, 2018; Brynjolfsson and McElheran, 2016).

3.1 Digital transformation and STEM work

Studies on digital transformation consistently shows that AI adoption tends to polarize employment outcomes (Aiello, 2024; Simkute *et al*., 2024). While demand increases for highskill roles capable of leveraging AI, many routine and entry-level positions are at risk unless graduates are adequately prepared to complement AI capabilities. For STEM trainees, this creates a growing mismatch between educational preparation and workplace expectations, especially around creativity, problem-solving, and adaptive thinking (Jang-Tucci *et al.*, 2024). This underscores the relevance of examining early-career STEM professionals' experiences, as they are often the first to confront the practical implications of AI integration. Despite substantial attention to AI's impact on labor more broadly (Benbya *et al.*, 2024; Engström *et al.*, 2024), relatively little research explores how STEM graduates experience and respond to these transformations during their initial career stages.

3.2 Developing AI-related skills

In response to these shifts, the cultivation of AI-related skills [1] has become a key focus in STEM education and workforce development. These include not only technical proficiencies such as data analysis, machine learning, and algorithmic thinking, but also broader competencies like ethical reasoning and systems thinking (World Economic Forum, 2025). However, training programs often struggle to keep pace with evolving industry requirements. Recent findings indicate that technical upskilling alone is inadequate; workers must also develop soft skills – such as but not limited to adaptability, strategic decision-making, and collaborative capacities for working alongside AI systems (Chaturvedi *et al.*, 2025). These insights highlight the complexity of skill development in AI-MWPs and call for a more integrated understanding of human-AI collaborations that goes beyond narrow technical training (Flathmann *et al.*, 2024).

3.3 Training needs for STEM graduates

Despite ongoing initiatives, there remains limited knowledge about how STEM graduates themselves perceive their training needs in AI-MWPs. Existing programs are predominantly shaped by organizational or educational institutions, often without incorporating the lived experiences of graduates navigating these environments (Simón *et al.*, 2024). This gap is particularly salient given that much of the empirical literature on AI-related skill development centers on mid-career professionals or generalized workforce samples. Reviews by Chaturvedi *et al.* (2025) emphasize trust, adaptability, and decision-making as crucial dimensions of human-AI collaboration, yet little is known about how these factors manifest in the formative early-career phase of STEM professionals. Consequently, there is a need to examine how recent STEM graduates interpret and respond to AI-induced changes in their work contexts – and how this shapes their professional identity and future learning trajectories.

In sum, while the broader discourse provides important insights into AI's macro-level effects on jobs and skills, it overlooks how early-career STEM professionals internalize and engage with these changes. Understanding their perspectives is vital to aligning educational and organizational efforts with the realities of AI-MWPs.

4. Methodology

4.1 Participants

Participants were university students aged between 20 and 29 (Mean = 21.2 [2]) who had undertaken Pflichtpraktikum (mandatory traineeship [3]) which was integrated into the curriculum and took place either in the second or third year. The STEM school was not directly involved in the traineeship process; rather, its role was limited to ensuring placement quality and setting and overseeing academic expectations.

Participants were studying STEM-related fields at a German public university in 2024. Most of them completed their traineeships in Germany whereas some did in other European countries, USA, Asia and the UK They worked in 246 different organizations, ranging from medium-sized firms to multinational corporations to research institutes, including prominent tech companies (e.g. Siemens, SAP), manufacturing firms (e.g. BMW, Henkel) and globally recognized research institutions (e.g. Max Planck, Fraunhofer). Work teams varied in size and function, and participants undertook a variety of technical, analytical, and research-oriented roles, depending on their field of study and the organization they joined. Roles included software development, cybersecurity analysis, DevOps, machine learning, human resources, procurement, mechanical design, automation, system optimization, materials testing, renewable energy analysis, and lab experimentation. The university had determined that all traineeships provided graduate-level employment before students started their placements.

A purposive sampling method suitable for our qualitative study was used (Bakkalbasioglu, 2020). All trainees ($N = 342$) were required to write a reflective essay as part of their formative traineeship assessment and were subsequently invited to participate in the study. No incentives were offered, and it was made clear that the study was unrelated to assessment (marking had already been done), participation was voluntary, and they could withdraw at any time. This approach was approved by the university's research ethics committee. A total of 325 trainees (95%) consented to their essays being analyzed. Survey data collected alongside the essays provided contextual information about the sample's working arrangements.

Among our sample, a diverse range of working arrangements and experiences emerged, reflecting Germany's structured yet flexible approach to professional development. In tech companies, for instance, where some interns collaborate in agile teams, contributing to software deployment, AI training, or cybersecurity, others in manufacturing firms, usually rotate between design labs, production floors, and testing facilities, refining prototypes or optimizing automation systems. Some, placed in renowned research institutions like Max Planck or Fraunhofer, engage in scientific experimentation, deep-learning simulations, or renewable energy analysis, often working in interdisciplinary teams with pre- or post-doctoral researchers.

An online poster inviting all trainees to participate in an interview about their work experiences was distributed. Subsequently, 45 interested participants received additional information, including consent forms, and a participant information sheet outlining the study's objectives, research goals, and ethical commitments. Of these, 40 agreed to participate in interviews. The interviewees represented various roles, industries, and organizations and had diverse work and study arrangements. No participants were compensated for their time.

4.2 Interviews

This research adopted a qualitative approach (Tarnoki and Puentes, 2019). Semi-structured interviews () Appendix 2 were conducted with 40 students who completed paid traineeships lasting between three and six months, and 325 reflective essays written by trainees about their work experiences were analyzed. These two data collection methods were chosen to allow participants to deeply reflect on and authentically express their experiences and perceptions in their own words (Hosein and Rao, 2017). The interviews aimed to gather detailed insights into trainees' work experiences from a subset of the broader sample, while the reflective essays assessed how their work experiences influenced the development of their competencies, work values, and life goals. The interviews provided an opportunity to explore specific AI-mediated work themes that emerged in the essays in greater depth and contributed to the triangulation process.

Focusing on trainees' own perceptions of employability was a deliberate choice, as they are ultimately the ones competing for jobs and opportunities. If they do not recognize their competencies or feel inadequate, this poses a challenge for STEM schools' employability missions (Hughes and Davis, 2024).

In-depth interviews were conducted with a subset of participants at the end of their traineeships. These interviews were conducted one-on-one with a researcher and lasted between 45 and 60 min. The discussions explored participants' AI-MWP experiences, covering aspects of their life and work routines, professional roles and characteristics, collaboration experiences with both humans and AI, and learning and development processes, including formal and informal training, onboarding experiences, development opportunities, and job proficiency.

At the end of the traineeship, participants wrote reflective essays assessing how their experiences and insights gained during the traineeship influenced their personal development. They were asked to write a 4,000-word essay on the development of their competencies, workplace values, and goals. Since students (i.e. trainees) were not explicitly asked to reflect on AI-MWP, any references to this topic emerged from their perception as an integral part of their job experience and development process.

4.3 Thematic data analysis

A total of 325 reflective essays and 40 semi-structured interviews were analyzed using thematic analysis. Thematic analysis was chosen as it is well-suited for identifying, analyzing, and reporting patterns (themes) within qualitative data, aligning with our research objective of exploring trainees' experiences and perceptions. This was based on the "systematic combining" approach described by Dubois and Gadde (2002), which involves a cyclical and interdependent process of "matching" and questioning reality and theory. This approach was chosen for its compatibility with abductive reasoning (Dubois and Gadde, 2002), balancing inductive insight with STS theory. The process unfolded in several key stages, each building on the last.

4.3.1 Phase 1: familiarization and initial coding. First off, we got familiar with the data by reading through the interview transcripts and reflective essays multiple times. This helped us get a feel for the overall narrative and tone. Following this, line-by-line and paragraph-level open coding was conducted using a constant comparative method. This allowed for initial impressions to be translated into descriptive codes such as decision support, workflow integration, responsible use, learning, and social cues. MAXQDA software was used to facilitate the systematic organization and coding of the large volume of qualitative data. MAXQDA was preferred over alternatives due to its ability to integrate memoing, coding, and literature simultaneously. In practice, the whole process resembled the grounded theory method, focusing on identifying themes within the data without relying on predefined theories. The process involved reading and comparing transcripts, followed by developing an iterative coding scheme (Gioia *et al.*, 2013).

4.3.2 Phase 2: axial coding and theme development. Next, we moved on to making sense of how these codes fit together. Axial coding allowed us to cluster related codes under more abstract constructs and identify patterns across data sources. Through iterative discussions, we refined the emerging structure into five high-level competency themes that captured the AI-MWP context: These were: (1) AI-mediated problem-solving and decision-making; (2) human-AI collaboration and adaptability; (3) ethical and responsible AI use; (4) data literacy and AI model awareness; and (5) interdisciplinary and lifelong learning. This evolving thematic map was reviewed multiple times to ensure consistency and to verify that the themes remained grounded in the raw data.

4.3.3 Phase 3: selective coding and interpretation. To keep things on track and consistent, selective coding was employed to synthesize and condense the findings. This involved re-examining the coded data within each theme and summarizing key insights using concise phrases or at times concept tags. This step enabled us to link the competencies directly to the participants' experiences with AI tools in the AI-MWPs. During this phase, particular attention was paid to ensure coherence across interview and essay data and to identify convergence or divergence in the emerging themes.

4.3.4 Ensuring reliability and consistency. To enhance the reliability of the analysis, several validation strategies were used. First, investigator triangulation was applied as two researchers independently coded the data and compared their interpretations regularly. Coding discrepancies were discussed and resolved collaboratively to reach consensus. Second, a codebook was developed and iteratively updated throughout the analysis to ensure consistency in how codes and categories were applied. Third, we conducted peer debriefing sessions with external qualitative researchers who were not directly involved in data collection to challenge and refine our interpretations. Finally, the consistency of the coding structure was verified across different data sources (interviews and essays), and no gender-based differences were observed.

4.3.5 Theoretical integration. After establishing the core themes, we further scrutinized the data to explore how and why these competencies manifested within AI-MWPs. This deeper analysis led to the identification of three interconnected characteristics of AI-MWPs that influenced competency development: (1) Information sharing – the capacity of AI systems to enable new forms of data access and insight. (2) Interaction process – how trainees engage with AI systems and adapt their work practices. (3) Involvement and ownership – the degree to which trainees feel accountable and take initiative in AI-mediated workflows.

These three features fed into the five competencies and helped us make sense of the broader picture. Altogether, the process gave us a solid and nuanced understanding of how trainees are navigating the shift through AI-MWPs (see Figure 1). The following section provides a detailed analysis of these three core findings. To ensure clarity, excerpts from reflective essays and those from interviews are marked as "[re]" and "[int]", respectively.

5. Findings

5.1 AI-mediated work experience

While some participants held strong and polarized views on the impact of AI on their work competency, others assessed its advantages and disadvantages more evenly. Many reported facing unique challenges as they entered the workforce for the first time. These challenges clustered around five high-level competencies: (1) AI-mediated problem-solving and decision-making; (2) Human-AI collaboration and adaptability; (3) Ethical and responsible AI use; (4) Data literacy and AI model awareness; (5) Interdisciplinary and continuous learning.

Our findings led to an AI-Mediated Workplace Impact Model (Figure 2) demonstrating how AI features (e.g. predictive analytics, smart tools) reshape workplace characteristics (information sharing, interaction, and ownership structures). The model illustrates the interconnections among these findings and highlights cascading pathways that link AI technologies to emergent challenges in professional adaptation. The following section discusses these characteristics and their impact on trainees' high-level competencies in finer detail.

5.2 Understanding AI-mediated analytics and decision-support tools

Participants reported that AI-MWP facilitated their ability to leverage data-driven insights and decision-support tools (C1). While some described AI recommendations as "helpful but impersonal" [int], "too rigid" [re], or "lacking nuance" [int], the use of analytics platforms and forecasting models mediated and generated by AI were found to be useful in optimizing workflows and decision-making. For example, AI-assisted forecasting tools helped participants identify trends and automate routine decision processes as they reported to have engaged with AI recommendations through real-time dashboards, automated reports, and algorithmic predictions.

The AI-mediated decision-making process was reported to support efficiency because they could: (1) receive real-time suggestions and analyze large datasets quickly; (2) revisit AI-generated insights, adjusting parameters to refine recommendations; (3) integrate AI's feedback into decision workflows, reducing the likelihood of errors. However, while AI tools improved analytical capabilities, they posed significant challenges in contextualizing recommendations within broader strategic goals. One participant reflected this as:

> I see what the AI says to do, but honestly, I don't always get why it picks that or how it fits with what we're trying to achieve overall. [int]

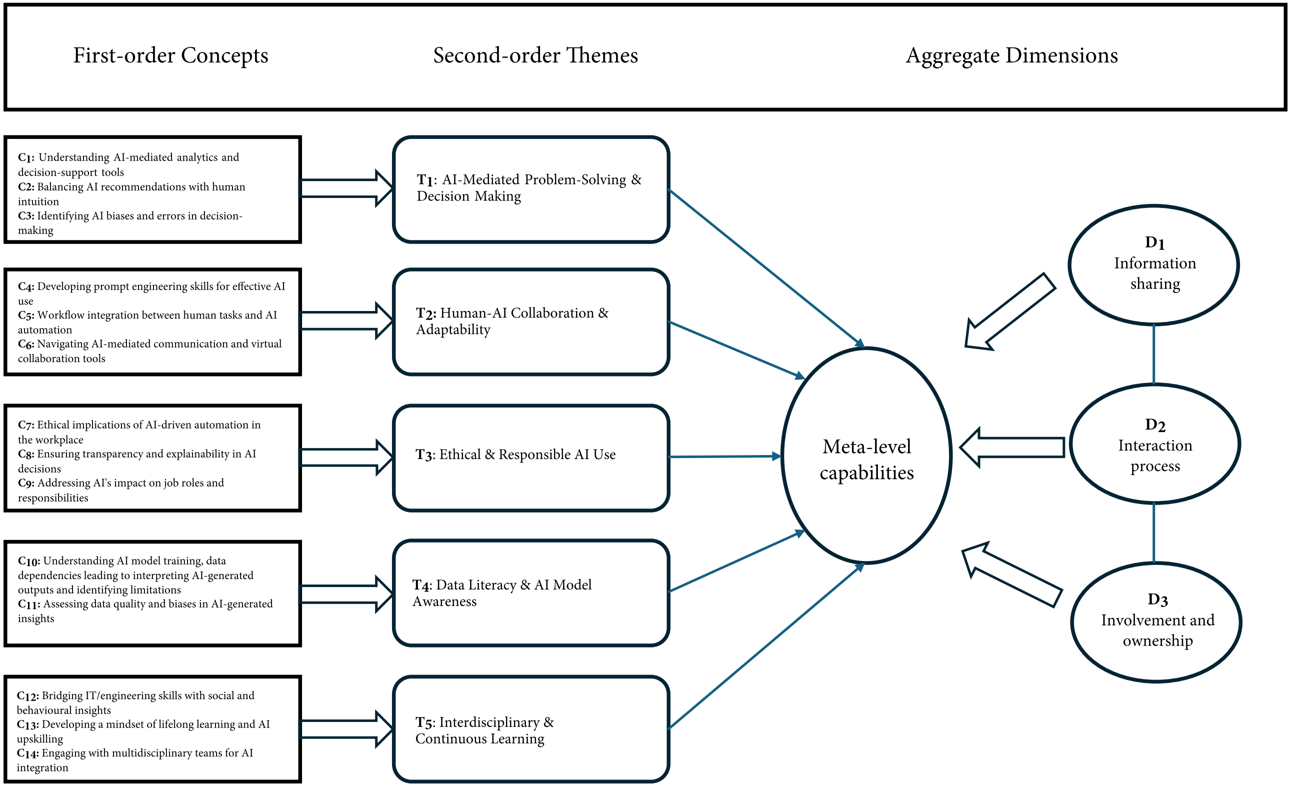

Figure 1. Thematic data analysis report. Source: Authors' own work

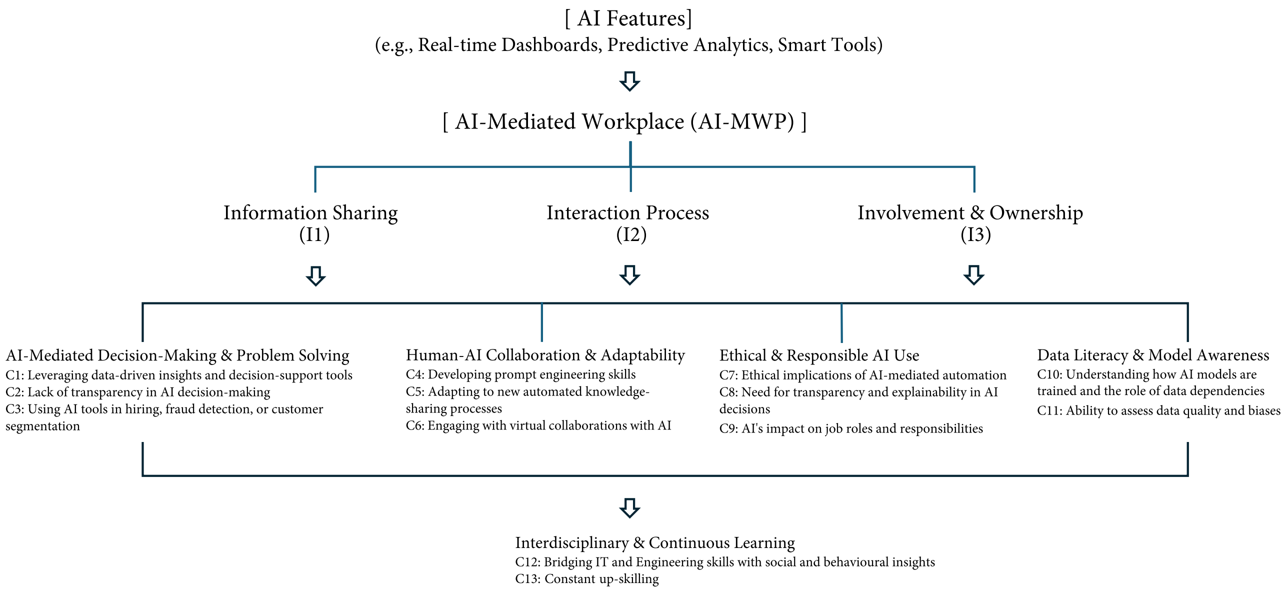

Figure 2. AI-mediated workplace impact model. Note: Arrows show influence and feedback loops. I1, I2, I3 are AI-MWP workplace mechanisms. C1–C13 are core trainee challenges/competencies shaped by these mechanisms. Source: Authors' own work

Others mentioned that they struggled to interpret AI-generated outputs without additional context. For example, one participant realized several months into their role that the automated sales projections produced by AI decision tools often required human intervention to account for qualitative market dynamics. He believed that their initial over-reliance on AI negatively impacted their decision-making credibility within the team. In this context, the AI-MWP created a new distinction between "trusting AI" and "understanding AI." Others also recorded to have needed explicit guidance on when to challenge AI recommendations and integrate their own domain expertise to refine decisions.

5.3 Balancing AI recommendations with human intuition

Participants noted that the lack of transparency in AI decision-making made it difficult to trust or challenge recommendations (C2). For instance, when AI-mediated hiring platforms filtered applicants without transparent reasoning, participants experienced doubt:

> I couldn't see why AI picked some resumes and not others, so I ended up double-checking everything myself . . . Made me wonder if it's really helping. [int]

In performance management too, frustration arose. One participant, who had been working on strategic, long-term projects, explained:

> I was building stuff for the long haul, but AI kept sayin' I wasn't hittin' short-term goals, so it made me look bad on paper. [int]

These instances highlighted that human intuition, context, and critical review were essential to correct or reframe outcomes mediated by AI.

5.4 Identifying AI biases and errors in decision-making

Trainees also became aware of biases when using AI tools in hiring, fraud detection, or customer segmentation (C3). For known biases, one participant shared:

> AI kinda repeats old mistakes 'cause it learns from past data that ain't perfect. [re]

For unknown biases, another trainee reflected after trusting AI-based CRM systems without question:

> At first, I just went with whatever AI told me. Later, I realized it kept favoring certain customer groups without good reason. [re]

They acknowledged the importance of questioning AI outputs and recognized human oversight as critical. As one participant summed up:

> AI gives me a good start, sure, but I always double-check it. It's a tool, not a replacement for thinking. [int]

5.5 Human-AI collaboration and adaptability

Information exchange increasingly occurred through AI-enhanced virtual collaboration tools (e.g. AI-powered chatbots, smart email filters, automated meeting summarizers, and virtual assistants). Face-to-face interactions became infrequent, and when they did happen, they were often preceded by extensive engagements between the interns and the AI that structured and pre-filtered communication.

While AI-mediated communication tools offer advantages for workplace collaboration (see Table 1), they also introduced new challenges in information flow. First, they required professionals to develop prompt engineering skills (C4) to effectively extract relevant insights from AI systems. Second, they changed the structure of human-AI workflow integration,

Table 1. Meta competencies and challenges identified by participants

Meta-competency	Challenges	Example data
AI-Mediated Problem-Solving and Decision-Making	a. Contextualizing AI-generated recommendations within strategic goals b. Difficulty in interpreting AI-generated insights within broader business or organizational strategies. Decision-makers struggle to bridge the gap between AI outputs and long-term goals c. Over-reliance on AI for decision-making without critical assessment d. Users tend to accept AI outputs without questioning underlying biases or misalignments, leading to potential suboptimal or unfair decisions	"I know what the AI suggests, but I don't fully understand why it recommends this approach or how it aligns with our overall strategy." [int] "AI suggests a strategy, but it's not clear how it was derived, making it hard to trust or integrate into strategic planning." [re] "I trusted AI's recommendation without question at first, but then I noticed that it systematically prioritized certain customer segments over others." [re] "AI disproportionately favors a specific demographic or market segment, and users only recognize the bias after reviewing long-term results". [int]
Human-AI Collaboration and Adaptability	a. Limited transparency in AI decision-making, requiring manual intervention b. AI's lack of explainability forces human intervention, leading to inefficiencies and trust issues c. AI-mediated performance metrics misaligning with human contributions d. AI-generated performance assessments fail to capture qualitative contributions, creating frustration and misaligned incentives	"Since I couldn't see the reasoning behind AI's decisions, I had to manually review resumes to ensure the right candidates weren't overlooked . . ." [int] "The AI hiring system filters out resumes, but hiring managers manually review candidates due to concerns about AI missing key qualifications." [int] "KPI system (AI-based) rewards short-term efficiency, but employees working on long-term strategic goals feel undervalued." [int] "I was optimizing for long-term success, but AI measured my output in a way that didn't reflect my contributions." [int]
Ethical and Responsible AI Use	a. Unclear justification behind AI-generated evaluations b. AI evaluations often provide numerical scores or classifications without sufficient reasoning, leaving employees unable to contest or understand their results c. AI's role in decision-making creating ethical dilemmas d. AI is used in high-stakes decisions (e.g. hiring, credit approvals, law enforcement), raising concerns about fairness, bias, and accountability	"I got an AI-generated evaluation, but I had no idea why I was rated lower than my colleague. There was no explanation—just a number." [int] "People receive AI-generated performance ratings but lack visibility into the factors influencing their scores." [re] "AI takes over certain decisions, but we don't always know if it's considering all the right factors. There's no human intuition involved." [re] "AI rejects loan applications but doesn't consider exceptional cases that a human would recognize, leading to unfair outcomes." [int]

(*continued*)

Table 1. Continued

Meta-competency	Challenges	Example data
Data Literacy and AI Model Awareness	a. Difficulty in assessing the quality and biases of AI-generated insights b. Users struggle to evaluate whether AI models rely on high-quality, representative data or reinforce existing biases c. AI reinforcing pre-existing biases d. AI models trained on biased data perpetuate discrimination or social inequalities, requiring careful oversight	"We trust AI's results too much, but how do we know if the data [it learned from] is even relevant?" [int] "AI recommends actions based on outdated or biased datasets, but users lack the expertise to validate its conclusions." [int] "We use AI-generated reports, but I've noticed sometimes they reinforce existing biases rather than challenge them." [re] "AI hiring recommendations favor certain demographics due to biased historical hiring patterns." [int]
Interdisciplinary and Continuous Learning	a. Gaps between technical and human-centered AI understanding b. AI experts and domain specialists struggle to communicate effectively, leading to misalignment between AI capabilities and business needs c. The need for ongoing AI upskilling due to rapid technological evolution d. AI technologies evolve quickly, requiring continuous learning for professionals to remain competent e. Challenges in cross-disciplinary collaboration due to differing expertise levels f. Effective AI implementation requires collaboration between data scientists, business leaders, and domain experts, but communication barriers often arise	"The AI folks get the tech part fine, but they don't always think about how it actually hits people. We need both sides talkin'." [re] AI engineers optimize an algorithm for efficiency but overlook real-world ethical or practical concerns raised by users. [int] "AI is evolving so fast. What I learned last year is already outdated. If I don't keep learning, I'll fall behind." [int] "An employee trained on an older AI tool struggles to adapt to a new version with different capabilities." [int] "We work with data scientists, but sometimes they assume we understand all the technical terms. There's a gap we need to bridge." [re] "A marketing team struggles to interpret AI-generated insights because the data science team assumes technical knowledge." [int]

Source(s): Authors' own work

requiring users to navigate automated knowledge-sharing processes (C5). Third, they influenced how the trainees had built relationships and engaged with AI-enhanced virtual collaboration environments (C6). These aspects are explored below as logistical challenges and power dynamics.

5.5.1 Logistical challenges. Participants who previously worked in traditional office settings reported learning through "passive absorption", whereas those in AI-MWP had to actively engage AI systems to retrieve necessary information. All participants noted that their learning experience depended on their ability to craft effective prompts for AI systems:

> I used to overhear key discussions in the office and naturally pick up new strategies, but now I must explicitly ask AI to generate summaries or insights. It's not as seamless. [int]

AI-mediated delivery of knowledge through automated summaries and recommendation algorithms also reduced spontaneous conversations, as communication became pre-structured and focused on efficiency:

> When I reach out to someone, it's usually to request specific insights or get AI-generated reports. The casual "water cooler" discussions don't happen because interactions are pre-scheduled or guided by AI chat recommendations. [int]

This shift had several consequences. First, it affected knowledge accessibility – since AI-mediated conversations were narrowly task-oriented, interns hesitated to ask broader contextual questions. Second, AI-mediated interactions sometimes felt impersonal:

> Talking to a chatbot for meeting notes is efficient, but it doesn't replace organic discussions with colleagues. [re]

Third, participants found that AI-assisted onboarding systems structured introductions to new team members but lacked the spontaneity of in-person networking. Over-reliance on AI to suggest relevant contacts and resources made relationship-building slower and fragmented:

> AI suggests whom I should connect with, but I don't always know if they are the right people to talk to—without office visibility, I can't organically expand my network. [int]

Moreover, AI-mediated communication reinforced hierarchical formality:

> Reaching out to senior colleagues is harder now. In a physical office, I could casually approach them, but sending an AI-assisted email or message feels too formal and deliberate. [re]

Fourth, participants worried that over-reliance on AI-mediated work allocation and reporting tools might limit their career growth and learning opportunities:

> With AI handling workflow automation, I need to be more proactive about demonstrating my skills. If I don't actively prompt AI systems to showcase my work, I remain invisible. [int]

To succeed in an AI-MWP, trainees had to develop strong prompt engineering skills (C4) and actively integrate AI tools into their workflow (C5) rather than passively consuming information.

5.5.2 Power dynamics. The AI-mediated shift in communication patterns altered workplace power structures. In some cases, human-AI collaboration platforms democratized access to information, allowing trainees to join virtual discussions they previously would have been excluded from due to physical constraints. Additionally, automated transcription and meeting summarization technologies served as an "equalizer" [int], ensuring that all voices were heard through automated meeting transcription and discussion summaries. However, trainees found it difficult to establish trust with colleagues, particularly in AI-managed workflows where visibility depended on how well they integrated AI-generated insights into their work.

> I realized I was just a passive observer in AI-driven meetings, mostly consuming automated summaries rather than actively engaging. [re]

Participants identified several barriers to career growth in AI-MWP, including (1) visibility challenges, (2) perceived availability issues, and (3) a lack of informal networking. AI-mediated workflows often led to trainees being overlooked unless they actively showcased their contributions, making them feel "invisible" [re]. Additionally, automated task assignment by AI tools created the perception that supervisors were too busy for mentorship or networking, limiting organic career development opportunities and making it difficult for trainees to correct this assumption due to their restricted visibility. The absence of unstructured office conversations, on the other hand, hindered the development of professional relationships, reducing exposure to new projects and collaborations. As AI-mediated communication and decision-making tools became central to workflows (C6), trainees recorded to have navigated these complexities by proactively managing their visibility, trust-building efforts, and engagement strategies.

5.6 Ethical and responsible AI use

Participants expressed concerns about the ethical implications of AI automation in the workplace (C7), highlighting both benefits and risks. While AI streamlined processes and reduced manual workloads, some felt it created ethical dilemmas, particularly around fairness in decision-making and the displacement of human roles. One participant, rated lower than peers by an AI system, expressed frustration, emphasizing the need for transparency and explainability in AI decisions (C8):

> Got an AI performance score, but it just gave me a number, no reasons, no feedback, nothin'. [int]

Others highlighted how AI took over tasks like resume screening or project assignments but lacked nuance:

> AI makes choices fast, but who knows if it's actually thinking about the right stuff? No gut feeling involved. [re]

This lack of insight may have left trainees feeling vulnerable, particularly in high-stakes scenarios such as performance assessments or hiring processes.

Participants also discussed AI's impact on job roles and responsibilities (C9), with some fearing job displacement, while others saw opportunities for role expansion. One trainee reflected:

> I used to do these tasks manually, but now AI does it. I had to find new ways to add value, or I'd just be redundant [re]

Many believed AI would not replace jobs outright but would require workers to shift toward higher-level problem-solving and oversight roles.

5.7 Data literacy & AI model awareness

Understanding how AI models are trained and the role of data dependencies in shaping AI-generated outputs (C10) was a recurring concern. Participants worked with AI-generated reports daily, from customer insights to risk evaluations. But they questioned the training data:

> We act like AI knows everything, but half the time, who even checks if the data's right? [int]

Many acknowledged that biases could exist in AI outputs but felt ill-equipped to identify or mitigate them. The ability to assess data quality and biases (C11) was seen as a critical skill, yet one that was rarely taught. One participant observed:

> Sometimes AI just repeats bad patterns, and unless you catch it, you won't even notice.[re]

This highlighted the need for organizations to invest in AI literacy training to help employees interpret outputs rather than accept them blindly.

5.8 Interdisciplinary and continuous learning

Bridging IT and engineering skills with social and behavioral insights (C12) was seen as essential for effective AI integration, yet trainees often felt that technical and human aspects remained siloed. One participant remarked:

> The AI team understands the tech, but they don't always get the human impact of their models. We need both perspectives. [re]

They also realized the need for constant upskilling (C13):

> Honestly, what I learned about AI last year already feels old. If I stop learnin', I'm screwed [int]

Collaboration across technical and non-technical roles remained challenging, but necessary for success:

> Working with data scientists is cool, but sometimes it feels like they expect us to just get all the tech jargon right away. We're still learning too. [re]

These findings emphasized the need for cross-disciplinary collaboration and a mindset of continuous learning to navigate AI-MWP effectively.

6. Discussion

6.1 Theoretical contributions

Our findings provide evidence that AI-MWP practices reshape the information-sharing, interaction processes, involvement, and ownership experiences of STEM graduates entering the workforce (Research Question 1). These transformations call for new training needs, which we classify into meta-competencies and challenges (Research Question 2), summarized in Table 1 Our findings offer novel insights into how these environments reshape interaction, learning, autonomy, task ownership, and professional development. Below, we detail five core theoretical contributions.

6.1.1 Extending socio-technical systems theory into AI-MWP contexts. Our study extends STS theory to AI-MWP, as we demonstrate how novel socio-technical dynamics (e.g. algorithmic work segmentation and AI-mediated communication) shape newcomers' engagement with their own work and with others. These developments illustrate how AI technologies are not neutral tools but embedded systems that reorganize workflows and restructure knowledge and communication flows. As such, AI-MWP challenges the foundational assumption of joint optimization by prioritizing efficiency and automation, sometimes at the expense of informal learning and social cohesion.

6.1.2 Socio-digital skills as a missing link in socio-technical frameworks. A key theoretical contribution of this study is the identification of *socio-digital skills* which are not limited to using digital tools but extend to interpreting AI outputs, assessing algorithmic logic, and collaborating across human-machine and interdisciplinary boundaries (Hughes and Davis, 2024). Our participants reported that while they were technically capable, they often lacked the contextual knowledge to make sense of their roles within broader workflows. This finding challenges the prevailing assumption that digital competence is sufficient for AI-era employability and suggests that socio-digital fluency (developed through social learning and interpretation) is critical. Our study thereby addresses a blind spot in socio-technical systems theory, which often focuses on macro-level alignment but pays less attention to individual, interpretive learning processes.

6.1.3 Reshaping learning, autonomy, and task ownership. Our findings reinforce and extend socio-technical principles related to autonomy, feedback, and task significance (Cherns, 1987; Bednar and Welch, 2020). In AI-MWP, features such as micro-tasking, automated task allocation, and performance feedback systems led to fragmented work experiences among trainees. These systems reduced visibility into broader workflows, making it difficult for newcomers to understand how their tasks contributed to team or organizational goals.

The loss of task interdependence and contextual clarity diminished perceptions of ownership and autonomy. While trainees could complete assigned tasks, they often did so passively following AI-generated prompts rather than exercising proactive judgment. This mechanistic approach to work limited opportunities for experiential learning, especially the development of anticipatory skills and problem-solving capacities associated with autonomous roles (Wall *et al.*, 1992; Erez, 2010). Thus, our study expands socio-technical theory by identifying how AI systems may unintentionally suppress the very conditions needed for developmental learning and autonomy-building.

6.1.4 AI-mediated communication and the disruption of informal structures. Another major finding relates to how AI-MWP impacts communication and collaboration. Participants reported that AI-mediated tools (e.g. automated meeting summaries, task notifications, and recommendation systems) promoted structured, transactional exchanges but suppressed spontaneous, informal interactions. These tools streamlined task management but reduced opportunities for passive learning, socialization, and mentorship.

This aligns with insights from social information processing theory, which posits that in ambiguous situations, individuals rely more heavily on social cues for *meaning-making* (Salancik and Pfeffer, 1978). In AI-MWP, however, digital interfaces filtered or stripped such cues, contributing to "unknown unknowns" for trainees. Without emotional context, political nuance, or informal role modeling, newcomers struggled to understand unwritten norms or expectations. Our study integrates social information processing theory with socio-technical thinking, offering a more nuanced account of how communication technologies shape knowledge flows, role clarity, and social embeddedness in AI-mediated environments.

6.1.5 Reconsidering power, visibility, and development pathways. Finally, our findings reveal how AI-MWP reshapes organizational visibility, decision-making authority, and career development pathways – particularly for early-career professionals. Algorithmic structuring of communication and workflows often privileged top-down information flow and de-emphasized lateral or informal channels. This limited trainees' exposure to feedback, recognition, and developmental opportunities.

Participants reported reduced access to role models and fewer opportunities for informal mentorship, with AI systems mediating not only how work was done, but also how influence, recognition, and advancement were distributed (Barati and Ansari, 2022; Simkute *et al.*, 2024). These effects created a form of structural invisibility for newcomers, whose contributions and development needs were not always recognized within the system.

STS theory has long emphasized the importance of competency development during technological transitions (Clegg, 2000). However, it has underexplored how these transitions affect the *conditions* under which development occurs. Our study advances this discussion by showing that AI's restructuring of tasks and communication flows can inadvertently undermine key learning structures (particularly autonomy, visibility, and social learning) essential to early-career growth and workplace integration.

Organizations must move beyond purely technical considerations and actively attend to how AI systems mediate social dynamics, learning trajectories, and career development pathways. This includes embedding structures that compensate for the erosion of informal learning (e.g. mentorship programs, collaborative work design, and training in socio-digital skills). Next, we discuss them in detail.

6.2 Practical implications and educational needs

Our findings offer clear practical implications and highlight specific educational needs. First, given the widespread adoption of AI-mediated work and digital communication technologies in workplaces, we need to rethink what digital skill development means for today's STEM graduates. Recognizing the presence and acquisition of socio-digital skills is crucial for addressing the evolving work dynamics. Structured training in AI literacy, ethical AI use, and collaborative problem-solving can help bridge the gap between technical expertise and the ability to operate effectively within AI-mediated socio-technical systems. In particular, understanding how AI tools filter, prioritize, and sometimes depersonalize communication is essential for navigating these new work environments. By fostering these skills, organizations can better equip their workforce to leverage AI as an enabler of innovation rather than a source of workplace friction or exclusion. Instead of focusing solely on training graduates and new hires with new technical skills, we should concentrate more on equipping them with interpersonal and professional skills that help them understand how and what to learn during this critical early career stage. While the competencies emerging from this research are not entirely new, the traineeship experiences described in this study indicate that soon-to-be graduates may need a new variant or balance of traditional competencies to succeed in the workforce.

Thus, STEM schools must reconsider the concept of digital education and provide more detailed training that encompasses these socio-digital aspects (Hughes and Davis, 2024). They should also offer more comprehensive training to trainees and graduates, helping them anticipate or recognize challenges in AI-MWP. Such training may specifically address how AI mediation affects professional behaviors, such as feedback-seeking, informal learning, and network-building. The success of this approach will require a shift in how STEM schools facilitate employability and demand that recruiters and employers become more aware of the challenges graduates face when entering digitally challenging workplaces (Donald *et al.*, 2021). Previous research has shown that sustainable careers can be facilitated through collaboration between organizations and employers (Jackson *et al.*, 2022; Donald *et al.*, 2021; Narayanan *et al.*, 2010) because no single actor in the career ecosystem can address this issue alone (Hughes and Davis, 2024).

Our findings indicate that AI-MWP practices hinder graduate trainees' network parameters, perceptions of social capital, and ability to demonstrate proactivity – key components of human capital and perceived employability (Thompson, 2005) that are linked to career success (Wasko and Faraj, 2005). The use of AI systems to streamline or automate communications, task assignments, and updates minimized opportunities for spontaneous engagement, weakening relational bonds among coworkers. While this challenge is not unique to AI-mediated work, it is amplified by the reduced opportunities for informal interactions, mentorship, and spontaneous knowledge sharing that typically foster professional growth. As AI systems mediate workplace communication and task coordination (Anthony *et al.*, 2023) graduate trainees may struggle to cultivate meaningful professional relationships, limiting their ability to leverage social capital for career advancement. Building on the work of Hughes and Davis (2024) and Thompson (2005), this study highlights the need to do more in helping STEM graduates recognize the value of peer networks and understand how their peers and other ecosystem actors can contribute to their career capital (Chandler *et al.*, 2011; Angervall *et al.*, 2018).

Additionally, our findings present broader challenges related to social mobility and inclusion for schools and employers, underscoring the importance of agility in curriculum and program development. The transition to AI-mediated work may exacerbate existing inequalities among graduates, as students are now more reliant than ever on personal networks to recognize and understand the unwritten rules of the workplace. Similarly, our findings suggest that STEM trainees in our study used new technologies (including AI productivity tools and performance dashboards) to mask insecurities or create unsustainable new norms and standards. In this way, organizations may perceive performance standards as being met, even if trainees have not truly acquired competence – relying instead on family support. AI systems' ability to superficially enhance the visibility of performance (e.g. polished auto-generated reports, suggested responses) may hide underlying skill gaps, especially among less-resourced trainees. This creates additional challenges for those concerned with social mobility (Thompson, 2005) and should prompt actors in the socio-technical career ecosystem to consider how AI-MWP can be designed to foster equitable access to professional development opportunities. Without intentional interventions, such as structured mentorship, inclusive networking opportunities, and transparent evaluation criteria, workplaces risk reinforcing privilege by benefiting those with pre-existing social capital (Daly and Silver, 2008). STEM schools and employers must therefore collaborate to develop adaptive learning models that equip trainees with both technical skills and the tacit knowledge needed to navigate professional landscapes. By integrating socio-technical approaches that balance AI efficiencies with human-centered support structures, institutions may mitigate the risk of widening disparities and ensure that all trainees, regardless of background, can build sustainable careers. Simply placing disadvantaged students in good traineeships may not be enough to close the gap with their better-connected peers if it reduces opportunities to learn about workplace culture and norms.

This research reopens questions about the extent to which STEM schools are responsible for addressing these challenges and educational needs (Narayanan *et al.*, 2010). Traineeships play a crucial role in STEM education, serving as a bridge between theoretical knowledge gained in the classroom and practical experience in real-world organizations (White and

Smith, 2022). They provide students with essential practical skills and exposure to industry practices (Hughes and Davis, 2024). While traineeships offer opportunities for knowledge application in AI-MWP, we argue that the responsibility for ensuring fairness in such workplaces should rest with employers. STEM schools play a significant role in facilitating such discussions, but they do not have full control over the ecosystem (Donald *et al.*, 2021). This is reflected in the education needs outlined in Table 1.Employers themselves must take a more active role in the socialization and acquisition of new human-AI collaboration skills among their trainee and graduate populations.

For example, "access to development opportunities" requires employers to consider how they design, deliver, and promote developmental activities and programs arranged by AI, rather than merely expecting trainees or graduates to actively seek out and engage with these opportunities. This includes ensuring that algorithmic development tools (such as skill tracking platforms or AI-curated learning paths) are accessible, transparent, and supportive of personalized growth rather than merely reinforcing existing hierarchies. The relationship between universities and trainee employers should be viewed as a dynamic and symbiotic partnership within the career ecosystem (Hughes and Davis, 2024), where all parties share responsibility for providing trainees with valuable learning experiences, facilitating their transition from academia to the workforce, and addressing labor market needs (Narayanan *et al.*, 2010).

7. Limitations and future research

Like all studies, this research has its limitations. First, although participants were employed full-time as graduate trainees for up to six months, they had not yet formally graduated, meaning that unaccounted-for maturity effects may exist. Second, the sample was cross-sectional, and no data were collected from trainees or graduates before 2023, making it impossible to determine whether these challenges existed before the rise of generative AI.

While our findings provide new insights into emerging challenges for graduates and highlight the need for a revised focus on digital skill development, revisiting these questions with future trainee and graduate cohorts would help us understand how and to what extent graduate experiences are evolving.

Regarding social desirability bias, we acknowledge that self-reflective data inherently carries this risk, especially given that AI competence is a valued trait in professional settings. To mitigate this, several measures were taken: data were anonymized, participation was voluntary, and data collection occurred after academic grading to separate participation from assessment. Additionally, triangulation across interviews and essays provided further robustness. As this is a qualitative study, a statistical test for bias was neither applicable nor performed.

Since our study is grounded within the German context, the literature reviewed, and the discussion are intentionally framed to align with the socio-technical and organizational characteristics prevalent in Germany and similar Western settings. We fully acknowledge that AI adoption trajectories and workplace norms may diverge significantly across global regions, particularly within the Global South. Expanding the discussion beyond our empirical scope risks overgeneralization or misrepresentation of contexts markedly different from our sample environment. Therefore, future research may examine how STEM trainees in diverse and developing contexts engage with socio-digital transformations where AI plays even a greater mediating role. Such comparative studies would not only complement but also extend the insights generated here. Additionally, although our findings did not reveal notable gender-based differences, the study did not systematically investigate other critical dimensions of intersectionality (e.g. race, socioeconomic status, or disability) which may shape individuals' experiences with AI integration. We encourage future research to explore these intersectional factors to build a more nuanced, inclusive, and generalizable understanding of the evolving nature of work in AI-mediated settings.

8. Conclusion

As STEM schools prepare graduates for future work, they must integrate socio-technical principles into workforce preparation, just as organizations designing future roles should embed these principles to support post-graduation transitions. Despite Generation Z's technical proficiency, higher education institutions and employers remain crucial in cultivating relevant digital work skills, particularly in the context of human-AI collaboration. Our findings emphasize the importance of listening to young professionals to identify skill gaps, challenge misconceptions, and refine education and hiring programs. After all, acquiring AI-mediated work skills represents a nuanced intersection of social and technical demands, underscoring the need to set trainees and graduates up for success in such work environments if they are to build thriving careers in this rapidly evolving landscape.

Appendix 1

Table A1. Basic demographical and country of internship statistics of participants

	Gender	Age
Mean	0.62	21.21
Standard Error	0.03	0.09
Median	1	21
Mode	1	20
Standard Deviation	0.49	1.54
Sample Variance	0.24	2.39
Kurtosis	−1.76	4.29
Skewness	−0.50	1.88
Range	1	9
Minimum	0	20
Maximum	1	29
Sum	202	6,892
Count	325	325
Country of Internship	Count	%
Germany	241	74.15
Europe (Other)	43	13.23
UK	18	5.54
Asia	15	4.62
USA	8	2.46
Total	325	100

Note(s): For Gender variable, Male = 1; Female = 0
Source(s): Authors' own work

Appendix 2

Interview Questions

(1) Life and Work Routines

Main Question 1:

Can you describe a typical day during your traineeship, particularly any parts that involved working with or around AI tools or systems?

Follow-up Questions:

How did your routine change over time as you gained more experience?

Were there specific tasks that consistently involved AI systems?

(2) Professional Roles and Characteristics

Main Question 2:

Howli would you describe your role and responsibilities during the traineeship?

Follow-up Questions:

To what extent did AI influence the scope or nature of your responsibilities?

Did the presence of AI require you to adopt new skills or mindsets?

(3) Collaboration with Humans and AI

Main Question 3:

Can you share an example of a situation where you collaborated with both human colleagues and AI systems?

Follow-up Questions:

How did the dynamics differ between human and AI collaboration?

Did you find it easier or harder to trust AI compared to human colleagues? Why?

Main Question 4:

Were there moments when the AI's output clashed with human input or judgment? If so, how was that handled?

(4) Learning and Development Processes

Main Question 5:

What kind of training (formal or informal) did you receive to help you work effectively with AI tools?

Follow-up Questions:

How useful did you find the onboarding process in preparing you for AI-related tasks?

Did you feel there were gaps in the training or areas where you had to self-learn?

Main Question 6:

How did you continue developing your AI-related knowledge or skills throughout the traineeship?

Follow-up Questions:

Were there any informal learning moments, such as peer-to-peer learning or self-initiated experimentation?

How supported did you feel in your development journey?

(5) Job Proficiency and Growth

Main Question 7:

Do you feel that working with AI has enhanced or hindered your job proficiency? In what ways?

Follow-up Questions:

Are there specific tasks or competencies where AI made a noticeable difference in your performance?

Has this experience changed how you think about your future career or skill development needs?

Notes

1. Any skills associated with or influenced by AI (e.g. technical, ethical, or even managerial aspects)
2. See Appendix 1 (Table A1) for demographical statistics and country of internship information of participants.
3. Also referred to as "internships", "work placements" or "practicum", traineeships are a key feature of STEM degrees in Germany and are becoming increasingly common across disciplines globally. The traineeship forms an integral part of Germany's dual education system and industry-academia collaboration representing extended work experience supported by the school, and its completion contributes to the final degree classification or title. In most cases, student traineeships provide their first major workplace experience and serve as an excellent representation of early-career employees, as new graduates share similar requirements.

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