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From tool to teammate: a conjoined agency perspective on cross-cultural acceptability of AI as a co-worker

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Abstract

Artificial intelligence (AI) is increasingly recognised as a transformative force driving technological advancements, particularly within organisations and the workforce. As AI tools continue to evolve, their role is shifting from mere instruments to collaborative co-workers that complement human efforts. This paper presents a comprehensive research agenda focused on understanding the acceptability of AI as a dynamic co-worker rather than just a tool. The objective is to explore how AI enhances productivity, decision-making, and overall workplace efficiency through human–technology collaboration. Drawing on the Technology Acceptance Model (TAM) and the Conjoined Agency Perspective, a cross-sectional survey was conducted with 858 professionals across 80 countries. The study reveals that AI acceptance is influenced less by demographic factors such as gender or culture and more by factors such as familiarity, understanding, and confidence. The findings also suggest that AI's role as a co-worker spans a spectrum of human–technology interactions, from assistive to more autonomous collaborations. Interestingly, acceptance of AI is not significantly affected by fears of automation or replacement concerns. This study offers one of the earliest cultural analyses of AI as a co-worker, positioning its integration as both a social and organizational process. The results provide practical guidance for policymakers and international organizations, emphasizing the importance of AI assistive, confidence-building, and addressing workforce concerns to promote inclusive and culturally sensitive human–AI collaboration.

Keywords AI acceptability, AI co-worker, AI teammate, Cross-cultural acceptance

1 Introduction

The contemporary workplace is undergoing an unprecedented transformation as artificial intelligence (AI) moves from being regarded as a technical tool to being conceptualized as a collaborative partner capable of augmenting human capabilities [38]. This paradigm shift requires organisations to develop adaptive strategies for the effective integration of AI into workflows, fundamentally redefining the relationship between humans and machines [7]. While early adoption of workplace AI focused largely on automation



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and efficiency gains, the emergence of generative AI and large language models has shifted the conversation toward more sophisticated forms of collaboration. Increasingly, AI systems are not only supporting human decision-making but also being perceived as co-workers in their own right [5].

The adoption of AI in the workplace is influencing both organisational practices and the human experience of work. As technology advances, individuals are required to collaborate not only with colleagues but also with AI technologies to achieve complex goals [24]. This shift represents a move from traditional human–computer interaction toward more nuanced forms of human–AI teaming, which demand new frameworks for understanding acceptance, trust, and collaboration [15].

The global nature of today's organisations adds complexity to this transition. Experiential learnings, cultural values and organisational contexts significantly influence how AI technologies are perceived and accepted [16]. Cross-cultural studies reveal clear differences in expectations, trust, and assessments of risk and benefit. In some contexts, AI is embraced with optimism, while in others, caution prevails [23]. National and cultural identities play a critical role in shaping adoption patterns, highlighting the need for perspectives that extend beyond Western-centric viewpoints and reflect diverse worldviews [21].

Despite growing scholarly and policy interest in human–AI collaboration, much of the existing research has concentrated on technological capabilities and organisational outcomes [36]. Less attention has been paid to the human and experiential factors that determine whether AI is successfully integrated as a teammate. While AI can enhance efficiency and decision-making, the coexistence of human workers and AI systems raises important questions about trust, fairness, ethics, and shared responsibility. A particular gap exists in understanding how cultural variation shapes the journey from viewing AI as a tool to accepting it as a co-worker, especially in day-to-day workplace interactions [38].

This research seeks to address that gap by examining cross-cultural and conjoin agency perspectives on AI acceptance, focusing on attitudes, experiences, and the factors that facilitate or hinder the shift from tool-based to teammate-based conceptualisations of AI. Although interest in AI adoption is growing, few studies have systematically explored how acceptance differs across cultural contexts and organisational settings. By adopting a cross-cultural lens, this study contributes to both theoretical knowledge and practical guidance for organisations striving to foster effective and culturally sensitive human–AI collaboration.

The implications extend well beyond academia. For international organisations, policymakers, and technology developers, the challenge is not only to build technically advanced AI systems but also to ensure they are culturally inclusive and acceptable. Achieving the shared benefits of AI will require cooperation on governance, ethical frameworks, and capacity-building while respecting cultural diversity and institutional realities. Understanding how different societies and institutions perceive AI as a co-worker is therefore essential for developing inclusive technologies and management practices that can operate across borders, ultimately contributing to more effective, equitable, and harmonious human–AI collaboration worldwide.

2 Literature review

Artificial intelligence (AI) has moved rapidly from research laboratories into everyday organisational practice, reshaping the way work is carried out across sectors. From health care to marketing to public administration, AI applications are no longer experimental but integral to routine operations [17]. In medicine, diagnostic tools powered by machine learning assist clinicians in interpreting scans with greater speed and accuracy [13]. In commercial settings, automated systems are now used to tailor advertising campaigns [21]. Human resources departments also deploy AI to filter job applications, allocate tasks, and even provide performance feedback [34]. In agriculture, AI is being applied across the entire value chain, from production to markets, with the goal of improving efficiency, resilience, and sustainability. For example, AI tools help farmers decide the exact amount of water, fertilizer, or pesticide to apply, reducing waste and environmental harm [20].

Scholars have begun to investigate how reliance on AI affects the workforce, often describing it in terms of “AI use”, the degree to which employees incorporate AI systems into daily tasks [3, 38]. Evidence to date highlights several positive outcomes. Studies indicate that employees may perform tasks more effectively, develop new creative approaches to problem-solving, and report greater satisfaction with their work [27, 35, 38]. These findings mirror the optimism of many industry leaders who promote AI adoption as a pathway to enhanced productivity and worker empowerment.

Yet this dominant narrative presents only part of the picture. The broader implications for labour, equity, and well-being are less clear and remain under-researched. Initial evidence suggests that the pressure to constantly engage or accept AI tools in work roles may have unintended outcomes. Rana et al. [33], for example, document associations between transformational leadership, AI competitiveness, and firm performance and found that when AI-enabled process automation is pushed too far, it can actually weaken the impact of transformational leadership, leading to reduced performance. While these studies take an organisational perspective, they point to a wider set of questions about project outcomes, surveillance, autonomy, and the redistribution of skills within workplaces.

For global institutions and intergovernmental agencies, this literature underscores both opportunity and caution. AI has the potential to support inclusive growth, improve access to services, and address capacity gaps in health, education, and governance. At the same time, neglecting the risks could exacerbate inequalities, erode worker well-being, and create new forms of dependency [25, 33]. A more balanced research agenda, one that critically assesses acceptability alongside costs, will be essential to inform international guidelines, labour standards, and policies that place human dignity at the center of technological adoption. This study seeks to investigate a cross-cultural perspective on the acceptability of AI as a coworker.

3 Research gaps

Furthermore, Einola and Khoreva [16] conducted an interpretive case study in Finland using the paradox theory perspective, interviewing 170 employees and 150 customers. However, future research should extend beyond the organisational level by including representatives from the broader cross-cultural AI ecosystem, since workforce complexity spans multiple contexts.

Doven et al. [14] conducted a survey of 546 employees in the United Kingdom and Turkey using the Unified Theory of Acceptance and Use of Technology (UTAUT) and analysed the data with Structural Equation Modeling (SEM). However, future research should explore other technology acceptance models and extend the findings to additional country contexts for broader applicability. Similarly, in Ghana, Ofosu-Ampong et al. [29] applied the Technology Acceptance Model (TAM) using a survey of 140 participants analysed through SEM and regression and reported innovative integration of AI in education. However, future studies should involve larger participant samples and compare findings across developing and developed country contexts to improve generalisability.

Our study addresses this research gap (see Table 1) by highlighting the need for future research to broaden the scope of AI studies, including representatives from the wider cross-cultural AI ecosystem and exploring additional technology acceptance models across diverse country contexts.

3.1 Conceptual framework

Technology adoption has been explained through several theoretical frameworks, including the Technology–Organisation–Environment (TOE) framework, the Theory of Reasoned Action (TRA), the Diffusion of Innovation (DOI) model, the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), and Institutional Theory [2]. While each provides valuable insights, their applicability depends on the level of analysis—some focus on individual adoption [12], while others examine organisational adoption [28]. Among these, the TAM has received the strongest empirical support as a robust model for explaining user acceptance of technology [1], and thus forms

Table 1 Selected AI adoption studies

Article	Country	Theory	Sample and methodology	Research gaps
[16]	Finland	The paradox theory perspective	Interviewed 170 employees and 150 customers Interpretive case study	Inclusion of representatives of the broader AI ecosystems (cross-cultural) since workforce complexity extends beyond the organisation
[14]	United Kingdom (UK) and Turkey	Unified theory of acceptance and use of technology (UTAUT)	Survey of 546 employees Structural equation model (SEM)	Need to explore other technology acceptance models and extend the findings across countries to examine assistive technologies
[29]	Ghana	Technology acceptance model (TAM)	Survey 140 participants SEM and regression	Future studies should include larger participants samples and compare findings across developing and developed country contexts to enhance generalisability
[37]	United States of America (US)	Relational demography theory (RDT)	Survey of 347 and 422 warehouse workers Experimentation	Existing studies overlook other potential sources of AI perception and dissimilarity, such as place of origin, temporary group membership, abilities, and knowledge
[4]	US & UK	Social exchange theory	Survey of 800 employees Vignette-based experimental study	There is a need to examine how cultural differences shape perceptions and acceptance of AI technologies
[9]	China	Cultural hierarchy theory	Survey of 523 corporate employees SEM and multigroup analysis (MGA)	Anthropomorphic appearance of smart products (AI) undermined people's willingness to use

the theoretical foundation of this study in studying two key constructs – *Perceived Ease of Use (PEOU)* and *Perceived Usefulness (PU)*.

There have been several extensions of the Technology Acceptance Model (TAM), notably TAM2 and TAM3 [31], which refined the original framework by introducing additional constructs and moderating factors to better explain user behaviour. Studies conducted in developing countries have also demonstrated the applicability of both the original and extended versions [30]. Overall, TAM provides a robust theoretical foundation for examining AI adoption, especially in contexts where users' perceptions of usefulness and ease of use play a central role in shaping acceptance.

To deepen this understanding, this study integrates the conjoined agency perspective to complement TAM in explaining AI acceptance across cultures. As AI systems increasingly display decision-making capabilities, human–technology interactions have evolved into various forms of shared agency. *Conjoined agency* refers to the joint capacity of humans and technologies to act intentionally and purposefully together [22]. Building on this, Murray, Rhymer, and Simon [26] identified distinct forms of conjoined agency, each representing different degrees of human–AI collaboration and autonomy within organisational routines. The proposed framework (Fig. 1) provides a lens for interpreting how individuals accept AI as a co-worker, depending on whether it assists, augments, or automates aspects of their work.

4 Methodology

This study used a cross-sectional survey design to assess the acceptability of artificial intelligence (AI) as a coworker within an international development organisation. The approach was selected to gather diverse cultural perspectives during a specific time-frame, providing a snapshot of current attitudes, concerns, and familiarity levels with AI technologies. The survey method was well-suited to the study's goals, which focused on examining attitudinal, cultural, and experiential factors that influence acceptance, rather than establishing cause-and-effect relationships [10]. The methodology comprised three main stages: (i) identifying the study population and creating a sampling frame and reaching out to the English speaking population across the regions, (ii) conducting the survey across multiple regions, and (iii) performing statistical analysis of responses to

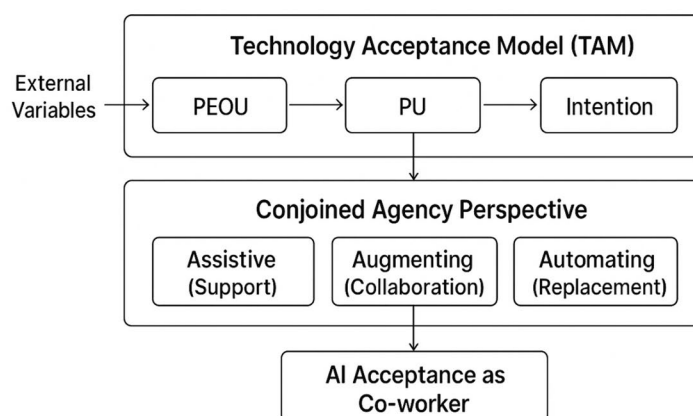


Fig. 1 Framework of TAM with conjoined agency perspective

find links between demographic, knowledge-based, and experiential factors and acceptance of AI as a co-worker.

4.1 Sampling and sample size

The study focused on professionals employed in large-scale organisations with at least 500 staff, operating within the international development and intergovernmental agency sector. This group was chosen because these organisations are increasingly using AI-enabled tools to enhance decision-making, operations, and service delivery, making them a key context for examining the dynamics of human–AI collaboration. A purposive sampling strategy was used to ensure representation from different cultural and institutional settings [18]. Participation was voluntary, with respondents invited through mailing lists, and professional networks channels. Their responses were kept confidential, ensuring privacy outside the study. The survey was distributed electronically to reach a broad cultural area, minimize logistical challenges, and promote inclusivity across countries with varying levels of digital infrastructure.

A total of 858 valid responses were collected from professionals in 80 countries. This sample size was deemed sufficient to ensure both statistical power for analysis and representation of diverse cultural and organisational backgrounds. Respondents displayed a broad demographic range, including gender, continent of origin, and varying levels of AI familiarity and use. The size and diversity of the sample enhance the external validity of the findings and provide a strong basis for drawing cross-cultural insights into AI's acceptance as a co-worker. To measure the experience of AI as co-worker in the workplace, seven questions were used and assessed using a 5-point Likert scale (strongly disagree, disagree, neutral, agree, and strongly agree). Furthermore, to ensure that the responses were comparable across countries, we used standardized measurement scales that have been validated across multiple cultural contexts [1]. This helped mitigate any variance caused by differences in the interpretation of questions.

4.2 Data collection

Data were collected through a structured online survey designed to assess awareness, usage, perceptions, and readiness related to AI, especially generative AI. The questionnaire (see Appendix: AI Readiness and Perception Survey) included both closed- and open-ended questions distributed across five sections: (i) awareness and understanding, (ii) current usage, (iii) perceptions and attitudes, (iv) readiness and skills, and (v) support and training needs. Respondents were required to provide informed consent before participating, and assurances of confidentiality were included in the survey introduction. This approach allowed for a broad cultural reach, enabling participation across diverse regions, including Africa, Asia, Europe, South America, and the Caribbean. Afterwards, the data were downloaded for cleaning and analysis. To maintain data quality, incomplete responses were excluded from the final dataset [8].

4.3 Data analysis

Quantitative data were coded and cleaned in Microsoft Excel before being imported into R studio for statistical analysis. Descriptive statistics, including frequencies, percentages, and cross-tabulations, were calculated to provide an overview of demographic characteristics, levels of AI awareness, and perceptions of AI as a co-worker. Inferential

statistics were used to test associations between key independent variables (e.g., gender, continent of origin, level of AI understanding, frequency of AI use, and organisational support) and the dependent variable of AI acceptance. Pearson's chi-square tests were performed to examine statistical significance across categorical variables. A p-value threshold of <0.05 was used to determine significance [19]. Open-ended responses were analyzed thematically to identify common patterns in opportunities, concerns, and perceptions of AI integration. Thematic analysis followed the six-phase framework outlined by Braun and Clarke [6], involving familiarization with data, coding, theme generation, review, definition, and reporting. These qualitative insights complemented the quantitative findings, providing deeper explanations of respondents' attitudes toward AI as a team member. The combined use of descriptive, inferential, and thematic analyses allowed for a comprehensive understanding of cultural acceptance patterns. Importantly, this mixed analytical approach enabled the study to go beyond surface-level usage metrics and explore deeper interpretations of knowledge, familiarity, and organisational context in shaping AI acceptance [11]. Ethical principles guided the design and execution of this study to ensure research integrity and participant protection. Participation in the survey was completely voluntary and confidential. The introduction of the instrument clearly stated the study's purpose, explained that responses would be used only for research, and assured participants of confidentiality.

5 Results

5.1 Acceptability of AI as a co-worker

A total of 858 workers from intergovernmental agencies across 80 countries participated in the study (Fig. 2 & Appendix). More than two-thirds expressed acceptance of AI as a co-worker, while 13.2% were uncertain about its acceptance and 2.4% reported non-acceptance (Fig. 3).

The main reasons cited for the uncertainty and non-acceptance of AI as co-worker included job displacement and workforce impact (28.4%), privacy, confidentiality and data security concern (19.4%), over-reliance and loss of critical thinking at the workplace (14.9%) and lack of knowledge, training and clear policies on AI (9.0%) (Table 2).

5.2 Socio demographic characteristics of respondents

Regarding gender, the highest proportion (59.8%) of the respondents were male (Tables 3).

The results indicate that the acceptability of AI as a co-worker is shaped less by demographic factors and more by levels of understanding and familiarity with AI technologies [32]. No significant differences were observed across gender ($p = 0.721$) or continent of

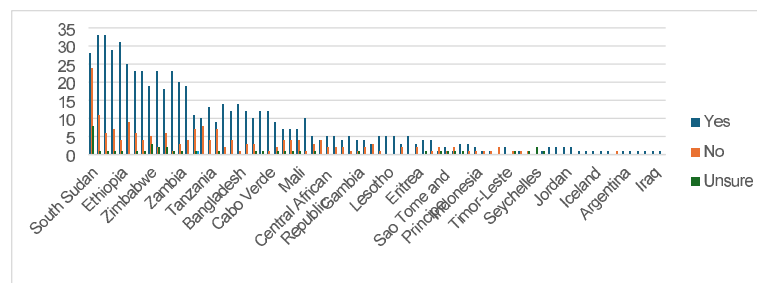


Fig. 2 Participants countries and use of AI in work

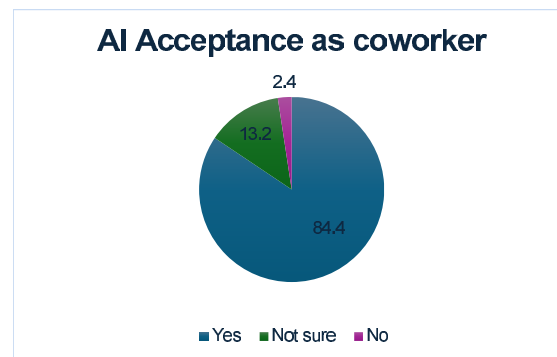


Fig. 3 Acceptance of AI as a co-worker

Table 2 Main reasons for the uncertainty and non-acceptance (n = 134) of AI as co-worker

	n (%)
Job displacement and workforce impact	38 (28.4)
A concern on privacy, confidentiality and data security	26 (19.4)
There is over-reliance and loss of critical thinking at the workplace	20 (14.9)
A concern on ethical, integrity and misinformation	18 (13.4)
There are still issues on accuracy and reliability of outcomes	15 (11.2)
Lack of knowledge, training and clear policies on AI	12 (9.0)
Other responses	5 (3.7)

origin ($p = 0.612$), suggesting that openness to working alongside AI is broadly shared across regions and demographics. In contrast, self-rated understanding of AI was significantly associated with acceptability ($p = 0.038$). Respondents with moderate to very high levels of understanding were far more willing to accept AI in the workplace than those reporting little or no knowledge. This highlights the importance of literacy and conceptual awareness in shaping positive attitudes toward AI. Interestingly, prior use of AI in work ($p = 0.171$) and frequency of use ($p = 0.125$) were not significantly linked to acceptability, indicating that mere exposure to AI tools does not necessarily translate into trust or willingness to work with them unless it is paired with deeper knowledge.

A second significant relationship emerged in connection with familiarity with generative AI tools such as ChatGPT, Copilot, or DALL·E ($p = 0.045$). Those who were very (92.6%) or somewhat (89.5%) familiar with these tools expressed greater acceptance of AI as a co-worker, while individuals who had only heard of such tools or were unfamiliar displayed higher levels of hesitation. This pattern suggests that firsthand, practical engagement with generative AI strengthens confidence and trust in AI's role in the workplace.

Moreover, the findings carry important implications for policy and practice. They show that cross-cultural acceptance of AI (84.4%) in work settings will not be achieved simply through greater access or routine use but rather through deliberate efforts to enhance AI literacy and promote meaningful familiarity. Education, awareness, and guided exposure are crucial for building the knowledge base that allows workers to understand AI's potential and limitations. The absence of significant differences across gender and regions further suggests that these challenges and opportunities are universal, opening the door for cross-culturally coordinated strategies to foster inclusive and confident adoption of AI in the workplace. In sum, the evidence underscores that acceptance of AI

Table 3 Socio demographic characteristics

Acceptability of AI as co-worker					
Variable	N = n (%)	Yes n (%)	Not sure (%)	No n (%)	p-value
<i>Gender</i>					0.721
Male	513 (59.8)	432 (84.2)	67 (13.1)	14 (2.7)	
Female	329 (38.3)	279 (84.8)	46 (14.0)	4 (1.2)	
Prefer not to say	16 (1.9)	13 (81.3)	2 (12.5)	1 (6.2)	
<i>Continent</i>					0.612
Africa	650 (75.8)	551 (84.8)	87 (13.4)	12 (1.8)	
Asia	123 (14.3)	107 (87.0)	14 (11.4)	2 (1.6)	
Near East	49 (5.7)	40 (81.6)	7 (14.3)	2 (4.1)	
Europe	31 (3.6)	21 (67.7)	7 (22.6)	3 (9.7)	
South America and The Caribbean	5 (0.6)	5 (100)			
<i>How would you rate your overall understanding of artificial intelligence (AI)? (PEOU)</i>					0.038*
Moderate	420 (49.0)	361 (86.0)	52 (12.3)	7 (1.7)	
Low	204 (23.8)	160 (78.4)	40 (19.6)	4 (2.0)	
High	167 (19.4)	150 (89.8)	10 (6.0)	7 (4.2)	
Very high	47 (5.5)	41 (87.2)	3 (6.4)	3 (6.4)	
No response	20 (2.3)				
<i>Have you used any AI tools in your work over the past 12 months?</i>					0.171
Yes	626 (73.0)	575 (91.9)	42 (6.7)	9 (1.4)	
No	188 (21.9)	124 (66.0)	54 (28.7)	10 (5.3)	
Not sure	44 (5.1)	26 (59.1)	16 (36.4)	2 (4.5)	
<i>How often do you currently use AI tools in your daily work?</i>					0.125
Occasionally	247 (28.8)	218 (88.3)	27 (10.9)	2 (0.8)	
Daily	245 (28.6)	238 (97.1)	5 (2.1)	2 (0.8)	
Rarely	129 (15.0)	97 (75.2)	26 (20.2)	6 (4.6)	
Never	126 (14.7)	69 (54.8)	46 (36.5)	11 (8.7)	
Weekly	103 (12.0)	99 (96.1)	4 (3.9)		
No response	8 (0.9)				
<i>How familiar are you with generative AI tools (e.g., ChatGPT, DALL-E, Copilot, Claude, Gemini)? (PEOU)</i>					0.045*
Somewhat familiar	436 (50.8)	390 (89.5)	39 (8.9)	7 (1.6)	
Heard of them, but don't use it	192 (22.4)	137 (71.4)	46 (24.0)	9 (4.6)	
Very familiar	148 (17.2)	137 (92.6)	9 (6.1)	2 (1.3)	
Not familiar at all	82 (9.6)	60 (73.2)	18 (22.0)	4 (4.9)	

$p < 0.1^{\dagger}$, $p < 0.05^{**}$, $p < 0.001^{***}$

as a co-worker depends less on who people are and more on what they know and how familiar they are with the technology, reinforcing the need for inclusive educational and policy measures to build trust in AI-enabled futures.

5.3 Experience with AI as co-worker

Furthermore, the analysis (Table 4) reveals that attitudes toward AI as a co-worker are shaped more by perceptions of its impact on jobs, organisational support, and individual confidence than by ethical concerns alone. Concerns about responsible and ethical use ($p = 0.177$) and data privacy ($p = 0.146$) were not significantly associated with acceptability, suggesting that while these issues remain important in public discourse, they do not directly influence willingness to work alongside AI. In contrast, those who expressed worry about AI replacing aspects of their job ($p = 0.001$) were significantly less likely to accept AI, underscoring the importance of addressing job security fears in policy and workplace strategies.

Table 4 Experience with AI as a co-worker

Acceptability of AI as co-worker					
Variable	N = n (%)	Yes n (%)	Not sure (%)	No n (%)	p-value
<i>I feel confident using AI tools responsibly and ethically. (PU)</i>					
					0.177
Agree	589 (68.6)	563 (95.6)	22 (3.7)	4 (0.7)	
Neutral	208 (24.3)	128 (61.6)	76 (36.5)	4 (1.9)	
Disagree	54 (6.3)	29 (53.7)	14 (25.9)	11 (20.4)	
No response	7 (0.8)				
<i>I am concerned about data privacy and security when using AI</i>					
					0.146
Agree	621 (72.4)	547 (88.1)	65 (10.5)	9 (1.4)	
Neutral	182 (21.2)	134 (73.7)	46 (25.3)	2 (1.1)	
Disagree	42 (4.9)	33	2	7	
No response	13 (1.5)				
<i>I am worried AI might replace certain aspect of my job</i>					
					0.001
Agree	341 (39.7)	287 (84.2)	48 (14.1)	6 (1.7)	
Neutral	282 (32.9)	223 (79.1)	52 (18.4)	7 (2.5)	
Disagree	235 (27.4)	214 (91.1)	15 (6.4)	6 (2.5)	
<i>My organisation should embrace AI to improve services and efficiency</i>					
					0.012
Agree	724 (84.4)	638 (88.1)	80 (11.1)	6 (0.8)	
Neutral	113 (13.2)	45 (39.8)	62 (54.9)	6 (5.3)	
Disagree	21 (2.4)	3 (14.2)	9 (42.9)	9 (42.9)	
<i>There is sufficient guidance in place to use AI ethically in my organisation (PU)</i>					
					0.105
Agree	724 (84.4)	229 (31.6)	337 (46.6)	158 (21.8)	
Neutral	113 (13.2)	20 (17.7)	66 (58.4)	27 (23.9)	
Disagree	21 (2.4)	3 (14.2)	10 (47.6)	8 (38.1)	
<i>How confident are you in your ability to learn and use AI tools effectively in your role? (PU)</i>					
					0.007
Very confident	355 (41.5)	334 (90.1)	17 (4.8)	4 (1.1)	
Somewhat confident	322 (37.5)	286 (88.8)	32 (10.0)	4 (1.2)	
Neutral	116 (13.5)	65 (56.0)	48 (41.4)	3 (2.6)	
Not very confident	57 (6.6)	37 (64.9)	14 (24.6)	6 (10.5)	
Not at all confident	7 (0.9)	3 (42.8)	2 (28.6)	2 (28.6)	
<i>Have you received any formal training or guidance on AI tools?</i>					
					0.015
Yes	170 (19.8)	158 (92.9)	12 (7.1)		
No	688 (80.2)	568 (82.6)	101 (14.7)	19 (2.7)	

$p < 0.1^*$, $p < 0.05^{**}$, $p < 0.001^{***}$

Organisational stance also mattered. Respondents ($n = 638$, 88.1%) who agreed that their organisation should embrace AI to improve services and efficiency were significantly more accepting ($p = 0.012$), highlighting the role of institutional leadership in shaping positive attitudes toward AI integration. Similarly, confidence in one's own ability to learn and use AI tools was a strong predictor of acceptance ($p = 0.007$). Those reporting high or moderate confidence overwhelmingly favoured AI as a co-worker, while those with lower confidence were more hesitant. Access to formal training further reinforced this relationship ($p = 0.015$), with trained individuals significantly more accepting than those without guidance.

Thus, the results suggest that acceptance of AI as a co-worker is driven less by abstract ethical concerns and more by practical factors—job security, organisational direction, individual skills, and access to training. For policymakers and organisations, this points to clear action areas: ensuring workers feel secure in their roles, investing in AI capacity-building, and providing structured training opportunities. Building confidence and aligning institutional strategies with ethical safeguards can foster a more inclusive,

prepared, and accepting workforce as AI becomes increasingly embedded in professional environments worldwide.

5.4 Correlational patterns in AI familiarity, use, and workplace acceptance

The correlation analysis (Table 5) highlights both expected and unexpected relationships in how respondents perceive and use AI. Most of the associations are weak, but several stand out as meaningful. An interesting finding is the negative correlation between familiarity with generative AI tools and actual use over the past 12 months ($r = -0.478$). This suggests that those who describe themselves as more familiar with tools such as ChatGPT or Copilot are not necessarily the ones using them in practice. Their familiarity may be based more on reading or hearing about AI rather than on direct, hands-on experience. Confidence emerges as a stronger driver of acceptance. Respondents who reported higher confidence in their ability to use AI tools responsibly were more likely to accept AI as a coworker ($r = 0.431$) and to agree that their organisation should embrace AI for efficiency ($r = 0.300$). Similarly, acceptance of AI as a coworker was strongly related to the belief that AI should be adopted organisationally ($r = 0.441$). These patterns suggest that confidence and ethical clarity act as gateways to wider acceptance of AI in professional contexts. Interestingly, there is a negative relationship between confidence in current AI use and self-rated ability to learn AI tools ($r = -0.273$). This may reflect a sense of overconfidence among some respondents who already use AI, or perhaps a perception that learning new tools is less necessary once one feels competent with existing ones.

Training also plays a significant role in shaping attitudes. Formal training or guidance on AI tools was positively related to AI acceptance ($r = 0.319$), reinforcing the view that structured support not only improves technical skills but also makes people more open to collaboration with AI. Similarly, training was positively associated with confidence in using AI ethically ($r = 0.142$), suggesting that exposure through training can strengthen responsible practices. Concerns about AI, such as data privacy and security ($r = 0.153$ with confidence) or fears of job replacement ($r = 0.222$ with privacy concerns), show weaker associations compared to confidence and training. While these concerns are present, they do not appear to be the main factors shaping adoption and acceptance.

Table 5 Descriptive statistics and correlation – AI acceptance as a co-worker

	Mean	SD	Gender	1	2	3	4	5	6	7	8	9	10	11	
Gender	1.46	0.667	—												
How would you rate your overall understanding of AI?	2.41	0.671	0.025	—											
How familiar are you with generative AI tools (e.g., ChatGPT, Copilot, Claude)?	2.63	1.01	-0.004	0.020	—										
Have you used any AI tools in your work over the past 12 months?	1.32	0.564	-0.020	-0.045	0.478	—									
How often do you currently use AI tools in your 1 work?	2.67	1.35	-0.040	0.039	-0.102	0.029	—								
I feel confident using AI tools responsibly and ethically.	1.56	0.659	0.046	-0.025	-0.206	0.287	0.059	—							
I am concerned about data privacy and security when using AI.	1.48	0.626	-0.030	0.011	-0.062	0.112	-0.061	0.153	—						
I am worried AI might replace certain aspects of my job.	1.93	0.653	-0.007	-0.051	0.001	0.046	0.025	0.112	0.222	—					
OUTREACH should embrace AI to improve services and efficiency.	1.37	0.746	0.005	0.008	-0.191	0.242	0.073	0.300	0.130	0.081	—				
There is sufficient guidance in place to use AI ethically in OUTREACH.	2.16	0.662	0.026	0.017	-0.060	0.045	-0.002	0.169	0.110	0.179	0.191	—			
How confident are you in your ability to learn and use AI tools effectively in your role?	4.13	0.924	-0.011	0.022	0.305	-0.210	-0.066	-0.273	-0.028	-0.066	-0.273	0.130	—		
Have you received any formal training or guidance on AI tools?	1.81	0.398	0.011	-0.013	-0.199	0.146	-0.003	0.142	0.056	0.019	0.105	0.139	-0.083	—	
AI Acceptance as coworker	1.29	0.664	0.008	0.026	-0.226	0.319	0.036	0.431	0.171	0.054	0.441	0.099	-0.330	0.093	—

Instead, they may represent background worries that coexist with more positive attitudes. In sum, the results suggest that awareness of AI is not enough to drive adoption or acceptance. The findings indicate that confidence, ethical assurance, and formal training are stronger predictors of whether people welcome AI in their work. Organisational strategies that emphasize practical training and responsible use may therefore be more effective in promoting AI adoption than efforts focused only on raising awareness.

5.5 Conjoined agency perspective of AI

Acceptance of AI as a co-worker reflects an evolving form of human–technology relationship, ranging from assistive decision support to more autonomous task execution. To theorize this shift, Murray et al [26] propose the framework of conjoined agency, which emphasizes that agency in human–AI work systems is not held exclusively by either humans or technologies, but is jointly configured through interaction. This framework distinguishes among assistive agency, augmenting agency, and automating agency, each of which carries distinct implications for employee acceptance and perceived threat.

From our study, we found the correlations between AI acceptance as a co-worker and concerns about AI replacing job aspects (replacement concerns) ($r = 0.054$, $p = 0.112$) as weak and statistically insignificant (Table 6). This suggests that employees' acceptance of AI does not strongly depend on whether they fear automation or job displacement. In terms of conjoined agency, this pattern reflects a tendency toward assistive or augmenting agency—i.e. employees may view AI as a supportive or collaborative tool rather than as a direct replacement (Table 7).

Similarly, the relationship between AI acceptance and confidence in working with AI ($r = 0.036$, $p = 0.286$) is also weak and non-significant. This implies that current confidence levels or familiarity with AI tools do not yet translate into strong perceptions of AI as a co-worker. It may indicate that employees have limited exposure to deeper, augmenting forms of AI collaboration, where humans and AI share tasks dynamically.

Overall, the absence of significant correlations suggests that most respondents experience AI in assistive rather than automating roles. Acceptance appears neutral, possibly because AI has not yet encroached on core job functions. Future studies could classify the specific conjoined agency types (assistive, augmenting, automating) to better explain variations in acceptance and perceived threat.

Consequently, the results of our study suggest that the future of *conjoined agency* between humans and artificial intelligence will involve deeper and more seamless integration, where the distinction between human and machine agency becomes

Table 6 Results of AI acceptance and conjoined agency

		AI Acceptance as coworker	Replacement concerns
Replacement concerns (I am worried AI might replace certain aspects of my job)	Pearson's r	0.054	
	df	856	–
	p-value	0.112	–
Confidence with AI (How confident are you working with AI as co-worker)	Pearson's r	0.036	0.025
	df	856	856
	p-value	0.286	0.471

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7 Conjoined agency types and interpretation of observed patterns .

Conjoined Agency Type	Description [26]	Example in Workplace Context	Expected Employee Perception	Observed Correlation Pattern	Interpretation
Assistive Agency	AI supports human work while humans retain control	Scheduling tools, report summarization	Generally positive; low perceived threat	Weak positive correlation between AI acceptance and worry about job replacement ($r=0.054$, $p=0.112$)	Acceptance is decoupled from job-replacement worry, suggesting AI is experienced as supportive
Augmenting Agency	AI and humans collaborate, sharing partial control	AI-assisted analysis, design, decision support	Cautious optimism with some uncertainty	Weak positive link between AI acceptance and confidence in working with AI ($r=0.036$, $p=0.286$)	Indicates limited exposure to augmenting AI—confidence does not yet drive strong acceptance
Automating Agency	AI performs tasks independently, potentially replacing human roles	Automated service or robotic processing	Often associated with insecurity and resistance	Non-significant correlation between fear of replacement and acceptance	Replacement concerns are not strongly linked to acceptance, suggesting low salience of full automation in current contexts

increasingly fluid. By combining human intuition and ethical judgment with AI's capacity for large-scale data processing and adaptive learning, this partnership holds the potential to drive transformative, responsible, and intelligent outcomes across all sectors of society.

6 Conclusion

The study demonstrates that acceptance of AI as a co-worker is not shaped by gender or culture but is strongly influenced by understanding, familiarity, and practical engagement with AI tools. Individuals with higher knowledge and greater exposure to generative AI expressed significantly greater openness, while job security concerns and lack of confidence emerged as barriers to acceptance. Furthermore, the results suggest that participants primarily engage with assistive forms of AI, where technology complements rather than replaces their work. The lack of significant correlations across variables reflects an early-stage or limited interaction with augmenting or automating AI forms. Future research should explicitly measure respondents' exposure to each conjoined agency type to better explain differences in acceptance and resistance. Together, these findings highlight the need for policies that expand AI literacy, provide structured training, and offer clear organisational guidance, ensuring that workers feel both prepared and secure as AI becomes an integral part of the workplace.

6.1 Recommendations for responsible AI integration as a co-worker

The study demonstrates that acceptance of AI as a co-worker is not shaped by gender or culture but is strongly influenced by knowledge, familiarity, and confidence in its use. Workers with higher AI literacy, greater exposure to generative AI tools, and access to training expressed significantly higher levels of acceptance, while job security fears and limited confidence emerged as barriers. These findings underscore the urgency of equipping organisations with clear frameworks and differentiated pathways for collaboration. The first priority is the development of an AI playbook that sets the ground rules for responsible collaboration. By defining institutional policies, risk checklists, and

approved systems, such a playbook reduces uncertainty, builds confidence, and normalizes AI as an accountable colleague rather than an invisible tool. Alongside this, organisations should invest in layered learning tracks—a foundational literacy program for all staff and advanced practice modules for power users who can mentor peers and model effective collaboration. This dual approach ensures both broad competence and the emergence of internal champions.

Equally important is the cultivation of a community of practice where early adopters serve as bridge colleagues, translating AI's potential into everyday routines and sharing grassroots innovations. Ethical and privacy safeguards should be embedded directly into existing workflows so that AI adheres to the same standards of responsibility expected of human co-workers. Also, proactive management of workforce identity and security is essential. Regular HR pulse surveys linked to reskilling initiatives can address concerns about job displacement, signalling that AI is being integrated as a collaborator that augments human potential rather than replaces it. Furthermore, future research should directly operationalize conjoined agency configurations through validated scales and multi-group cross-cultural comparisons. Such work can clarify when AI shifts from being perceived as an assistive teammate to being viewed as an automating substitute, and how these shifts shape acceptance trajectories across occupations, societies, and stages of AI maturity.

Organisations should position AI as a supportive partner rather than a threat, emphasizing its assistive value in improving efficiency and easing routine workloads. A gradual shift toward augmenting forms of human–AI collaboration can strengthen confidence and acceptance, particularly when employees are actively involved in shaping how AI tools are used. Transparent communication about automation plans and role changes helps reduce anxiety and builds trust. To sustain long-term adoption, organisations should invest in digital literacy and hands-on AI training that empower staff to work confidently alongside intelligent systems. Redesigning work processes to combine human judgment with AI capabilities, while embedding ethics and inclusion, will foster a culture of trust, learning, and innovation in the evolving workplace.

Appendix 1

Count of Location	Have you used any AI tools in your work over the past 12 months?			
	Yes	No	Unsure	Total
South Sudan	28	24	8	60
Ghana	33	11	1	45
Somalia	33	6	1	40
Uganda	29	7	1	37
Ethiopia	31	4	1	36
Kenya	25	9		34
Nepal	23	6	1	30
Hungary	23	4	1	28
Zimbabwe	19	5	3	27
Mozambique	23	2	2	27
Nigeria	18	6	2	26
Thailand	23	1	1	25
Zambia	20	3	1	24
Madagascar	19	4		23

Count of Location	Have you used any AI tools in your work over the past 12 months?			Total
	Yes	No	Unsure	
Malawi	11	7	1	20
Democratic Republic of the Congo	10	8		18
Tanzania	13	4		17
Papua New Guinea	9	7	1	17
Cameroon	14	2		16
Burundi	12	4		16
Bangladesh	14	1		15
Rwanda	12	3		15
Egypt	10	3	1	14
Bhutan	12		1	13
Cabo Verde	12	1		13
Chad	9	2	1	12
Equatorial Guinea	7	4	1	12
Niger	7	4	1	12
Mali	7	4	1	12
Angola	10	1		11
Burkina Faso	5	3	1	9
Senegal	4	4		8
Central African Republic	5	2		7
Sierra Leone	5	2		7
Gabon	4	2		6
Djibouti	5	1		6
Gambia	4	1	1	6
Botswana	4	2		6
Mauritania	3	3		6
Tunisia	5	1		6
Lesotho	5			5
Togo	5			5
Congo	3	2		5
Namibia	5			5
Eritrea	3	2		5
Viet Nam	4		1	5
Benin	4	1		5
Guinea-Bissau	1	2	1	4
Sao Tome and Principe	2	1	1	4
Liberia	1	2	1	4
Guinea	3		1	4
Afghanistan	3	1		4
Indonesia	2	1		3
Myanmar	1	1		2
Mauritius	1	1		2
Yemen		2		2
Timor-Leste	2			2
South Africa		1	1	2
Cambodia	1	1		2
Eswatini		1	1	2
Seychelles			2	2
Côte d'Ivoire	1		1	2
India	2			2
China	2			2
Jordan	2			2
Italy	2			2

Count of Location	Have you used any AI tools in your work over the past 12 months?			Total
	Yes	No	Unsure	
United States of America	1	1		2
Brazil	1			1
Iceland	1			1
Comoros	1			1
Morocco	1			1
Palestine		1		1
Argentina	1			1
Japan	1			1
Chile	1			1
Dominican Republic	1			1
Iraq	1			1
Mongolia	1			1
Grand Total	626	188	43	858

Supplementary Information

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Replace Table 5 with this document

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Data availability

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Declarations

Ethics approval and consent to participate

The study was conducted in accordance with applicable ethical guidelines. All participants gave written informed consent prior to taking part.

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