Annals of Medicine and Medical Sciences (AMMS)
Volume 05, 2026, *Page No.: 10 to 16*
Available at: *http://ammspub.com*

Original Article

Attitudes Toward Artificial Intelligence Among Technical and Non-Technical Employees: A GAAIS-Based Comparative Study

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Abstract

Background: The rapid integration of AI into workplaces highlights the need to understand employee attitudes influencing acceptance and use, yet multidimensional comparisons between technical and non-technical employees remain limited. ***Aim:*** To compare attitudes toward AI between technical and non-technical employees using the General Attitudes Toward Artificial Intelligence Scale (GAAIS), assessing both positive evaluations (e.g., usefulness, innovation) and negative concerns (e.g., errors, loss of control). ***Methodology:*** A cross-sectional study of 85 employees (technical = 58; non-technical = 27) using workplace AI assessed attitudes via the GAAIS and demographics; group differences were analyzed using Welch's t-tests with Hedges' g effect sizes visualized in forest plots. ***Results:*** Technical employees showed moderate Positive (3.65 ± 0.26) and lower Negative (2.99 ± 0.39) scores. Thirteen items differed significantly between groups, with non-technical employees exhibiting higher Positive and Negative subscale scores, reflecting greater attitudinal polarization and longer organizational AI exposures. ***Conclusion:*** Technical employees exhibited more stable, experience-based attitudes toward AI, balancing perceived benefits with lower levels of concern. These findings highlight their potential role as key stakeholders in responsible and sustainable organizational AI implementation.

Keywords: ***Artificial Intelligence, General Attitudes Toward Artificial Intelligence Scale (GAAIS).***

Introduction

Artificial intelligence (AI) has rapidly become one of the most influential technological forces shaping contemporary organizations. Defined as the ability of machines to emulate human cognitive processes, including reasoning, learning, and decision-making [1,2], AI is now woven into the fabric of modern business operations. Its widespread appeal lies in its capacity to automate routine tasks, optimize workflows, and augment human expertise, ultimately enhancing productivity and strategic performance [3,4]. As these technologies become embedded in organizational infrastructures, AI is transforming how work is performed, how decisions are made, and how innovation occurs.

The rise of AI is particularly pronounced in technology-driven sectors, where advanced algorithms, data analytics, and predictive modeling have become essential for maintaining competitiveness [5,6]. Generative AI tools, including ChatGPT, Copilot, and Gemini, have increased the AI adoption by supporting rapid and vast content creation, software development, and on-demand problem solving, and are now widely used by IT professionals to improve efficiency and reduce repetitive workload [7,8]. Despite their growing presence, research still shows a limited understanding of how employees form attitudes toward these technologies, especially in professional contexts undergoing rapid digital transformation [9,10].

The shift toward AI is not only reshaping organizational processes but also profoundly affecting the work experiences of employees. Automation, job redesign, skill displacement, and the need for continuous upskilling are creating new challenges for the modern workforce [11-13]. While AI allows some employees to shift toward more analytical and strategic responsibilities, freeing them from repetitive tasks, others view these changes with apprehension, concerned about job insecurity and the potential for workforce reduction [14]. These mixed reactions highlight that the impact of AI on work is neither uniform nor universally positive; instead, it varies widely based on employees' perceptions, experiences, and expectations.

In the IT sector—one of the earliest and most intensive adopters of AI—these concerns are particularly salient. The integration of intelligent systems requires employees to adapt to evolving roles, collaborate with AI-enabled tools, and continually update their skills. While technological capabilities continue to advance, the success of AI adoption ultimately depends on employee acceptance, trust, and readiness for change [15]. Understanding these

Received: December 02, 2025; **Revised:** December 24, 2025; **Accepted:** December 29, 2025

attitudes is therefore essential for ensuring effective technology implementation and supporting employee well-being.

To examine these perceptions systematically, the present study employs the General Attitudes Towards Artificial Intelligence Scale (GAAIS) a validated instrument that captures both positive evaluations of AI (such as opportunities for innovation and efficiency) and negative concerns (such as fears of errors, job loss, or reduced human control). By applying the GAAIS to IT employees, this study aims to provide deeper insights into how workers interpret the growing influence of AI in their professional environments and what factors shape their acceptance and use intentions.

Materials and Methods

Ethical Considerations

Ethical approval for the study was obtained from the Institutional Ethics Committee of Konaseema Institute of Medical Sciences, Amalapuram, Andhra Pradesh. Participants were informed about the study's objectives, confidentiality measures, and voluntary nature of participation.

Study Design

This study employed a cross-sectional, descriptive survey design to examine employees' attitudes toward artificial intelligence (AI) and their experiences of AI-related workplace stress. The design was chosen to capture perceptions at a single point in time across different employment sectors.

Participants and Sampling

Participants were recruited through purposive sampling from both the technology (IT) sector and various non-IT service sectors, focusing on employees who regularly interacted with AI tools as part of their work. A total of approximately 100 participants were surveyed, 85 participants were only included after considering the inclusion and exclusion criteria, with balanced representation across sectors. Eligible participants were adults aged 18 years and above, employed for at least six months in their current role, exposed to AI technologies in their daily tasks, and willing to provide informed consent were only included. Individuals who were not using AI at work, had less than six months of tenure, were on extended leave, or were unable or unwilling to provide consent were excluded from the study.

Instruments

Our study utilized the General Attitudes Towards Artificial Intelligence Scale (GAAIS), developed by Schepman and Rodway (2023) [16], to assess employees' overall attitudes toward AI, and permission to use the scale was duly obtained. This validated instrument measures both positive perceptions such as perceived benefits and opportunities and negative concerns, including fears of job loss, errors, and reduced human control. In addition to the GAAIS, supplementary items on AI-related workplace stress were incorporated to capture employees' psychological experiences associated with their exposure to AI technologies.

Data Collection Procedure

Data were collected through an online survey administered via secure digital platforms, including organizational intranets and email links. Participants provided electronic informed consent prior to participation. The survey remained open for a defined period to maximize response rates and accommodate working schedules. Confidentiality and anonymity were maintained, and respondents were informed of their right to withdraw at any time. Only participants who consented were included in the final dataset.

Data Analysis

GAAIS responses were summarized as means and standard deviations for the positive and negative subscales in technical and non-technical employee groups as per the author guidelines. Between-group comparisons were conducted using Welch's independent-samples t-tests to accommodate unequal sample sizes and heterogeneity of variances. Item-level outcomes were expressed as mean differences with corresponding t-values, degrees of freedom, p-values, and 95% confidence intervals. Effect sizes were estimated using Hedges' g to quantify the magnitude of group differences. Statistical significance was defined as $p < 0.05$ (two-tailed). Data quality was ensured through verification of scoring accuracy and completeness. Analyses were performed using Microsoft Excel and freely available online statistical tools for computation of means (SDs) and Welch's t-tests.

Results

Table 1: Demographics & workplace characteristics

Variable	Total (N=85)	Technical (n=58)	Non-technical (n=27)
Age (Years)			
• 18-25	27 (31.76)	22 (37.93)	05 (18.52)
• 26-35	38 (44.70)	25 (43.10)	13 (48.15)
• 36-45	11 (12.94)	07 (12.07)	04 (14.81)
• 46-55	07 (8.24)	02 (3.45)	05 (18.52)
• 56 and Above	02 (2.35)	02 (3.45)	00
Education			
• Bachelor	53 (62.35)	44 (75.86)	09 (33.33)
• Masters	29 (34.12)	14 (24.14)	15 (55.56)
• Doctoral	03 (3.53)	00	03 (11.11)
Experience in years			
• 0-2	27 (31.76)	20 (34.48)	07 (25.93)
• 3-5	23 (27.06)	17 (29.31)	06 (22.22)
• 6-10	12 (14.12)	10 (17.24)	02 (7.41)
• 11-15	09 (10.59)	05 (8.62)	04 (14.81)
• 16 and above	14 (16.47)	06 (10.34)	08 (29.63)
Work arrangement			
• Onsite	67 (78.82)	46 (79.31)	21 (77.78)

• Remote • Hybrid	05 (5.88) 13 (15.29)	03 (5.17) 09 (15.52)	02 (7.41) 04 (14.81)
Frequency of AI use • Daily / Often • Rarely • Sometimes • Very Frequently	 40 (47.06) 05 (5.88) 19 (22.35) 21 (24.71)	 27 (46.55) 02 (3.45) 15 (25.86) 14 (24.14)	 13 (48.15) 03 (11.11) 04 (14.81) 07 (25.93)
How long has the organization using AI tools • Not Yet Implemented • < 6 months • 6 – 12 months • 1-2 Years • 2 Years	 08 (9.41) 13 (15.29) 27 (31.76) 29 (34.12) 08 (9.41)	 06 (10.34) 07 (12.07) 19 (32.76) 19 (32.76) 07 (12.07)	 02 (7.41) 06 (22.22) 08 (29.63) 10 (37.04) 01 (3.70)

Table 1 summarizes the demographic and workplace characteristics of the 85 participants. Technical employees constituted 68.2% (n = 58), and non-technical employees comprised 31.8% (n = 27). Among technical employees, 81.0% were aged 18–35 years, and the group was predominantly male; the non-technical group showed a more balanced gender distribution and a wider age range. Educational attainment differed by role, with most technical employees holding bachelor's degrees, while non-technical employees displayed more varied qualifications. Overall, 78.8% of participants worked onsite. Organizational AI adoption was reported by 90.6% of the sample, with most indicating 6 months to 2 years of AI use. AI tool usage frequency showed that 47.1% used AI daily or often, and 24.7% used AI very frequently. The distributions of AI adoption duration and AI usage frequency were similar across technical and non-technical groups

Table 2: Attitudes toward Artificial Intelligence in technical employees: comparison with non-technical roles using GAAIS

S. No	Item	Item Polarity	Mean Difference (Δ)	$t^{\$}$ (Welch)	df	*p* value
1	For routine transactions, I would rather interact with an artificially intelligent system than with a human.	Positive	**+0.71**	3.29	81.0	**0.002**
2	Artificial Intelligence can provide new economic opportunities for this country.	Positive	**+0.57**	3.80	72.9	**<0.001**
3	Organisations use Artificial Intelligence unethically	Negative†	**+1.23**	5.64	79.9	**<0.001**
4	Artificially intelligent systems can help people feel happier	Positive	**+0.36**	2.04	57.2	**0.046**
5	I am impressed by what Artificial Intelligence can do	Positive	+0.27	1.72	73.8	0.090
6	I think artificially intelligent systems make many errors	Negative†	+0.24	1.27	71.6	0.208
7	I am interested in using artificially intelligent systems in my daily life.	Positive	**+0.41**	2.44	61.8	**0.018**
8	I find Artificial Intelligence sinister	Negative†	+0.60	3.06	69.3	**0.003**
9	Artificial Intelligence might take control of people	Negative†	**+1.18**	5.24	71.9	**<0.001**
10	I think Artificial Intelligence is dangerous	Negative†	**+0.81**	3.66	72.2	**<0.001**
11	AI can have positive impacts on well-being	Positive	+0.26	1.70	67.0	0.093
12	Artificial Intelligence is exciting.	Positive	+0.09	0.71	63.6	0.482
13	An artificially intelligent agent would be better than an employee in many routine jobs.	Positive	**+1.04**	4.76	73.7	**<0.001**
14	There are many beneficial applications of Artificial Intelligence	Positive	−0.08	−0.77	63.9	0.445
15	I shiver with discomfort when I think about future uses of Artificial Intelligence	Negative†	**+1.43**	6.22	70.5	**<0.001**
16	Artificially intelligent systems can perform better than humans	Positive	**+1.21**	5.73	73.4	**<0.001**
17	Much of society will benefit from a future full of Artificial Intelligence	Positive	+0.24	1.19	75.0	0.238
18	I would like to use Artificial Intelligence in my own job	Positive	+0.09	0.45	66.9	0.651
19	People like me will suffer if Artificial Intelligence is used more and more.	Negative†	+1.42	6.10	76.4	**<0.001**
20	Artificial Intelligence is used to spy on people	Negative†	**+0.82**	2.96	79.1	**0.004**

† Negative items were reverse scored; higher values indicate greater tolerance toward AI drawbacks. Δ = Mean Difference, $ Welch's independent-samples t-test, df = degrees of freedom, P=Two-tailed (p)

Table 2 shows, Item-level comparisons between technical (n = 58) and non-technical employees (n = 27) were conducted using Welch's independent-samples t-tests. Statistically significant group differences ($p < 0.05$) were found for 13 of the 20 items. Across all significant items, technical employees reported lower mean scores than non-technical employees.

For negative-attitude items, significant differences were observed for Item 15 (Δ = 1.43, t = 6.22, df = 70.5, $p < 0.001$), Item 19 (Δ = 1.42, t = 6.10, df = 76.4, $p < 0.001$), Item 3 (Δ = 1.23, t = 5.64, df = 79.9, $p < 0.001$), Item 9 (Δ = 1.18, t = 5.24, df = 71.9, $p < 0.001$), Item 10 (Δ = 0.81, t = 3.66, df = 72.2, $p < 0.001$), and Item 20 (Δ = 0.82, t = 2.96, df = 79.1, $p = 0.004$).

For positive-attitude items, significant differences were detected for Item 16 (Δ = 1.21, t = 5.73, df = 73.4, $p < 0.001$), Item 13 (Δ = 1.04, t = 4.76, df = 73.7, $p < 0.001$), Item 1 (Δ = 0.71, t = 3.29, df = 81.0, p = 0.002), Item 7 (Δ = 0.41, t = 2.44, df = 61.8, p = 0.018), and Item 4 (Δ = 0.36, t = 2.04, df = 57.2, p = 0.046).

No statistically significant differences between technical and non-technical groups were observed for Items 5 (p = 0.090), 6 (p = 0.208), 11 (p = 0.093), 12 (p = 0.482), 14 (p = 0.445), 17 (p = 0.238), or 18 (p = 0.651).

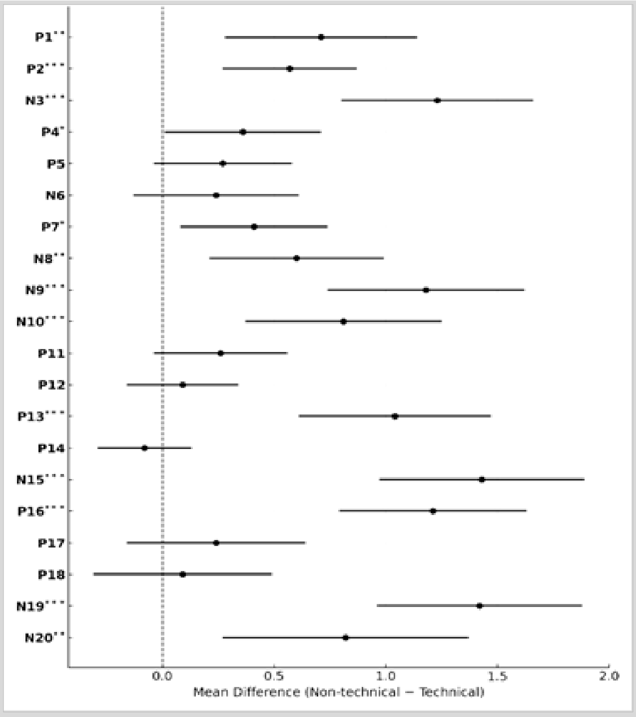

Figure 1. Forest plot displaying item-wise mean differences (Non-technical − Technical) with 95% confidence intervals

Figure 1 presents item-wise mean differences in GAAIS scores comparing technical employees (reference group) and non-technical employees, with mean differences calculated as non-technical minus technical scores and displayed with 95% confidence intervals. Statistically significant differences were observed for multiple GAAIS items, particularly for negative items N3, N9, N10, N15, and N19, for which confidence intervals did not cross the null value. Significant differences were also identified for positive items P1, P2, P4, P7, P13, and P16. For several items, including P5, N6, P11, P12, P14, P17, and P18, confidence intervals crossed zero, indicating non-significant differences between technical and non-technical employees. The forest plot summarizes the direction, magnitude, and statistical significance of item-level differences relative to the technical employee group.

While Table 2 reports item-wise mean differences (Δ) and inferential statistics (t, df, p), standardized effect sizes were synthesized at the subscale level, as shown in Figure 2, the Positive GAAIS subscale demonstrated an overall small-to-moderate effect favoring the non-technical group (Hedges' g = 0.72), whereas the Negative subscale exhibited a large effect (Hedges' g = 0.91), indicating substantially greater tolerance toward AI-related risks among non-technical participants.

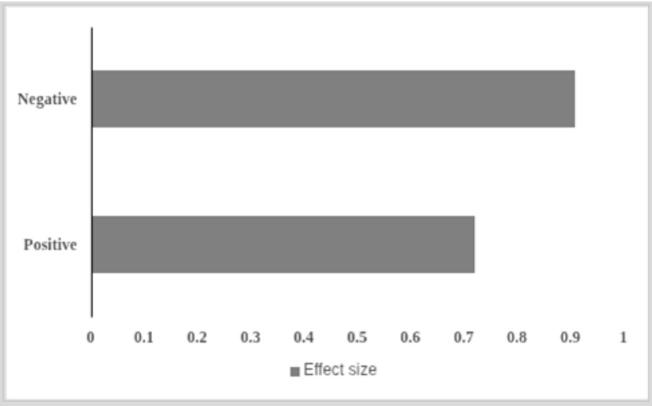

Figure 2: Effect size estimates (Hedges' g)

Figure 2 depicts the effect size estimates (Hedges' g) for differences between technical and non-technical employees on the positive and negative GAAIS subscales. The plot shows a clear separation between groups for both subscales, with larger effect sizes observed for the negative subscale compared to the positive subscale. Effect size estimates for the negative subscale exceeded those of the positive subscale, reflecting greater magnitude of group differences in negative attitude items. The effect size plot complements the item-level forest plot by summarizing the overall magnitude of between-group differences at the subscale level relative to the technical group.

Table 3: Comparison of Positive and Negative GAAIS subscale scores between technical and non-technical participants

Variable	Total (N=85)	Technical (n=58)	Non-technical (n=27)	Test (statistic, p)$
Positive subscale Mean (SD)	3.65 (0.45)	3.65 (0.26)	4.08 (0.18)	t ≈ −8.9, p < 0.001
Negative subscale Mean (SD)	2.99 (0.51)	2.99 (0.39)	3.97 (0.23)	*t* ≈ −14.5, *p*< 0.001

$ Welch's independent-samples t-test, P=Two-tailed (p)

Table 3 presents subscale-level GAAIS scores for technical employees in comparison with non-technical employees. For the Positive subscale, technical participants had a mean score of 3.65 ± 0.26, whereas non-technical participants had a higher mean score of 4.08 ± 0.18; Welch's independent-samples t-test indicated a statistically significant between-group difference (t ≈ −8.9, p< 0.001). Similarly, for the Negative subscale, the mean score among technical participants was 2.99 ± 0.39 compared with 3.97 ± 0.23 among non-technical participants, with this difference also reaching statistical significance (t ≈ −14.5, p< 0.001). Overall, subscale-level GAAIS scores for the technical group differed significantly from those of the non-technical group on both subscales (p< 0.001).

Table 4: AI Adoption Duration and Attitudinal Subscale Differences Between Technical and Non-technical Employees

Variable	Technical (n = 58) Mean (SD)	Non-technical (n = 27) Mean (SD)	Test (statistic, p) $
Years organization using AI (years)	2.0 (1.1)	3.7 (1.6)	*t* ≈ −5.1, *p*< 0.001
Positive subscale score	3.65 (0.26)	4.08 (0.18)	*t* ≈ −8.9, *p*< 0.001
Negative subscale score	2.99 (0.39)	3.97 (0.23)	*t* ≈ −12.0, *p*< 0.001

$ Welch's independent-samples t-test, P=Two-tailed (p)

Table 4 summarizes organizational AI adoption duration and corresponding GAAIS subscale scores for technical employees in comparison with non-technical employees. Technical employees reported working in organizations with a shorter duration of AI implementation (mean ± SD: 2.0 ± 1.1 years) compared with non-technical employees (3.7 ± 1.6 years), with the between-group difference reaching statistical significance ($p < 0.001$).

For the Positive GAAIS subscale, technical participants had a mean score of 3.65 ± 0.26, whereas non-technical participants reported a higher mean score of 4.08 ± 0.18. For the Negative subscale, technical employees reported a mean score of 2.99 ± 0.39, compared with 3.97 ± 0.23 among non-technical employees. Between-group differences for both GAAIS subscales were statistically significant ($p < 0.001$). Statistical significance indicates that the observed differences between technical and non-technical employees in AI adoption duration and GAAIS subscale scores are unlikely to be due to random variation alone ($p < 0.001$)

Discussion

This study examined attitudes toward artificial intelligence among technical employees using the General Attitudes toward Artificial Intelligence Scale (GAAIS). Technical employees demonstrated moderately positive evaluations of AI (Positive subscale: 3.65 ± 0.26), reflecting functional acknowledgment of efficiency and automation benefits without strong endorsement of AI superiority or replacement potential, consistent with prior evidence on performance expectancy and technology adoption [14,17-21].

Negative attitudes were comparatively lower among technical staff (Negative subscale: 2.99 ± 0.39), aligning with literature suggesting reduced anxiety and greater perceived control among technically experienced users [22-24]. These findings parallel prior reports linking balanced AI attitudes with better workplace well-being during technological transitions [12,14]. Technical employees also reported shorter organizational AI exposure than non-technical employees, while showing less attitudinal polarization, aligning with work highlighting the impact of AI maturity on employee well-being and reactions [25,26]. Their responses were consistent with established models linking openness, perceived usefulness, and facilitating conditions to technology acceptance [27-31]. The demographic profile of the technical group–predominantly bachelor's-level employees with relatively limited organizational tenure–aligns with recommendations to tailor AI deployment to educational background and experience [32].

We found from our study that technical employees function as stabilizing agents in AI adoption, offering grounded evaluations that neither exaggerate benefits nor amplify risks. In contrast, non-technical employees exhibited greater emotional polarization in their responses, whereas technical workers' attitudes reflected direct engagement with AI systems and an informed awareness of their limitations. The multidimensional structure of the GAAIS effectively captured this divergence by distinguishing functional optimism from affective anxiety.

Overall, these results position technical employees as a group with stable, experience-based attitudes toward AI, underscoring their organizational value as key stakeholders in AI governance, training, and change management to support responsible, transparent, and sustainable AI implementation.

Conclusion

Technical employees show a measured, experience-driven acceptance of AI-recognizing its practical benefits while expressing relatively low concern about its risks. This balanced perspective positions technical professionals as critical stakeholders for guiding effective and responsible AI adoption within organizations.

Limitations

This study used a cross-sectional design and purposive sampling of employees already exposed to AI tools, which may limit generalizability. The modest sample size and unequal group sizes (technical vs non-technical) may reduce statistical power for some comparisons. Self-report measures are susceptible to social desirability and common-method bias. Future research should include larger, more diverse samples, longitudinal designs, and qualitative methods to explore how workplace context shapes evolving AI attitudes.

Declarations

Ethical Clearance

The study was approved by the Ethical Committee.

Data Availability

All data available on corresponding author upon responsible request.

Funding source

None

Conflict of interest

No

Acknowledgment

The authors sincerely thank Dr. Astrid Schepman, Associate Professor, Division of Psychology, School of Society, University of Chester, United Kingdom, for granting permission to use the General Attitudes Toward Artificial Intelligence Scale (GAAIS) and providing the original scale and research manual for this preliminary study. The authors also extend their gratitude to all participants who willingly provided informed consent and actively participated in the study.

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