International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(18s) 2026 pp. 1431-1440
https://doi.org/10.70917/ijcisim-2026-4991
Article

# Employee Trust in Generative AI: Differences in Organizational Commitment and Engagement Across Employee Groups

**Dr. Jenifer Lawrence[1], Dagmawi Mandefro Abebe[2], Tilahun Haile Filatie[3], Dr. Rahamath Sulthana[4]**

[1]Associate Professor, Dept. Of. Management, Woldia University, Ethiopia. Email-aljeniferalbin@gmail.com.
[2]Lecturer, Dept. Of. Management, Woldia University, Ethiopia. Email- dagmawimandefro@gmai.com.
[3]Lecturer, Dept. Of. Management, Woldia University, Ethiopia. Email-Tilahunhaile4@gmail.com, Orcid:https://orcid.org/0009-0003.
[4]Assistant Professor, Dept. Of. Management Studies, B.S. Abdur Rahman Crescent Institute of Science and Technology, India. Email- rahamathsulthana@gmail.com.

**Abstract:** The increasing adoption of generative artificial intelligence (GenAI) in the workplace has raised important questions about how employee trust in AI relates to engagement and organizational commitment. The study examined the relationships among trust in GenAI, employee engagement, and organizational commitment using secondary quantitative data. Data were analyzed in IBM SPSS Statistics 27 using reliability analysis, descriptive statistics, Pearson correlations, independent-samples t-tests, one-way ANOVA, and multiple linear regression. The study measures demonstrated good to excellent reliability, with Cronbach's alpha values ranging from .811 to .945. Trust in GenAI was positively associated with organizational commitment ($r = .371$, $p < .001$) and employee engagement ($r = .470$, $p < .001$). Employee engagement was also positively related to organizational commitment ($r = .406$, $p < .001$). No significant differences were found across profession, education, or AI-tool groups, while gender differences were significant only for organizational commitment. The regression model explained 24% of the variance in organizational commitment, with employee engagement emerging as the strongest predictor, followed by trust in GenAI and gender. The findings highlight the importance of trust and engagement in supporting positive employee attitudes in AI-enabled workplaces.
**Keywords:** Generative AI; Employee trust; Employee engagement; Organizational commitment; Human resource management

## 1. Introduction

The use of artificial intelligence (AI) in human resource management (HRM) is becoming more prevalent, affecting how organizations recruit, assess, support, and manage their staff. AI-based systems are now helping organizations screen candidates, evaluate employees, plan the workforce, communicate with employees, and support decision-making, creating new opportunities for efficiency while also raising concerns about fairness, transparency, employee acceptance, and trust (Dima et al., 2024). With AI systems increasingly playing a role in workplace decisions, workers are no longer mere bystanders of technological change, as their attitudes toward AI systems can influence their reactions to both the technology and the organization implementing it (Bankins et al., 2024). In this regard, trust is especially critical, as workers might assess AI on its output, as well as whether its conclusions are reasonable, understandable, or appropriate. Lee (2018) demonstrated that perception of algorithmic decisions is closely associated with notions of fairness, trust, and emotion, indicating that the reactions and feelings of employees to the use of AI will be influenced by their interpretation of the decision-making process. In related areas of AI-based personnel selection, applicants' perceptions of justice also impact acceptance of AI-based selection systems (Acikgoz et al., 2020). There is also empirical evidence that the acceptance of AI is linked to the context in which it's applied.

Reactions to highly automated job interviews vary with regard to the stakes and the perceived importance of the situation (Langer et al., 2019). Similarly, employee responses vary depending on the level of technology in decisions made by humans, AI systems, or a combination of human and machine judgment, suggesting that the extent of technology in an organizational decision influences employee response (Gonzalez et al., 2022). The results underscore the need to explore trust in AI as an attitude in the workplace, not just a technical matter. In the field of HRM, the role of AI could be even more significant when it comes to employee trust, as HR functions are frequently linked to organizational support, fairness, and job security. Empirical evidence suggests that AI technology trust plays an important role in shaping employees' perceptions when artificial intelligence is integrated into HRM practices (Arora & Mittal, 2025). Besides, AI adoption is linked to employee performance and work engagement, indicating that technological change can impact employees' psychological engagement with work (Wijayati et al., 2022). AI-enabled work environments also have the potential to foster positive employee functioning, as does trust, according to more recent research, particularly when the use of AI meets employees' psychological needs (Watermann et al., 2026).

Trust in AI is also influenced by how AI systems are governed. Ethical governance, employee autonomy, privacy, and the responsible use of AI in HRM have become increasingly important. The findings indicate that increased ethical monitoring can contribute to employee trust and mitigate adverse responses like technostress (Patnaik et al., 2026). Studies on AI as an element in HRM systems also highlight the significance of trust and privacy in interpreting the outcomes of the workforce, which suggests that the reactions of employees to AI are driven not just by technology-specific but also organizational-specific circumstances (Shil et al., 2026). Accepting AI may have repercussions beyond the immediate. In a recruitment context, trust and procedural justice have been found to impact organizational attraction and intention to apply, suggesting that attitudes toward AI can impact attitudes toward the organization itself (Babaee & Shank, 2025). Additionally, AI-driven hiring decisions have been linked to the justice perceptions of applicants and their long-term organizational engagement, suggesting that perceptions of automated decision systems can impact longer-term organizational engagement and relationships (Yu et al., 2025). However, organisations are still using human judgement as well as algorithmic recommendations, and studies have found managers often reinterpret and modify algorithmic recommendations when deciding on hiring (Bursell & Roumbanis, 2024). Not all employee responses are adverse to algorithms. The perception of algorithms as being able to provide helpful, objective recommendations is one reason for sometimes preferring algorithmic judgments to human judgments (Logg et al., 2019). But this reliance on algorithms might rise where users have some control over changing or shaping algorithmic recommendations (Dietvorst et al., 2018). In addition, there are contextual variations in acceptance across tasks, meaning that employees might have varying reactions to AI depending on the type of task they are performing (Castelo et al., 2019). Additional insight into these responses comes from employee engagement. Engagement is a psychological investment in work and has been linked to positive attitudes and behaviours of the organization (Saks, 2006). Empirical studies also indicate that employees who are engaged are more involved and have better performance-related outcomes (Rich et al., 2010). In the work-engagement literature, the concept of vigor and dedication is an important element of employees' engagement and a helpful indicator of their energetic and psychological relationship with their work (Schaufeli et al., 2006). The current study aims to investigate trust in generative AI, employee engagement, and organizational commitment based on secondary quantitative employee data. The study will focus on the direct associations, employee-group differences, and predictive values of trust and engagement for organizational commitment.

***Objectives of the Study***

(1) To assess the levels of trust in generative AI, employee engagement, and organizational commitment.

(2) To examine the relationships among these three constructs.

(3) To determine whether these attitudes differ according to employee characteristics such as gender, education, profession, and AI-tool use.

(4) To examine whether trust and employee engagement significantly predict organizational commitment after accounting for age and gender.

***Accordingly, the following hypotheses are proposed:***

*H1: Trust in generative AI is positively associated with organizational commitment.*

*H2: Trust in generative AI is positively associated with employee engagement.*

*H3: Employee engagement is positively associated with organizational commitment.*

*H4: Trust in generative AI and employee engagement significantly predict organizational commitment.*

## 2. Methodology

### *2.1 Research Design*

The study employed a quantitative secondary data research design to explore the relationships between the variables of trust in generative AI, employee engagement, and organizational commitment. A cross-sectional study was conducted since the data are responses gathered at one point in time. The study examined direct associations among the main variables, differences across employee groups, and predictors of organizational commitment. Descriptive statistics, reliability analysis, Pearson correlation, independent-samples t-test, one-way ANOVA, and multiple linear regression were used for statistical procedures.

### *2.2 Data Source and Sample*

Secondary data were obtained from the *AIGenJan.xlsx* dataset available through the Figshare repository (Prasad, 2024). The original data were collected using a structured questionnaire covering generative AI, HRM practices, organizational commitment, employee engagement, employee performance, and employee trust. The questionnaire included measures of optimism, innovativeness, ease of use, usefulness, trust, organizational commitment, vigor, dedication, and employee performance. The dataset contains data from more than 450 respondents.

### *2.3 Variables and Measurement*

Only variables relevant to the present research objectives were included in the analysis. Four items (TST1–TST4) constituted the measure for trust in generative AI, and five items (OC1–OC5) constituted the measure for organizational commitment. Vigor (VIG1 – VIG3) and dedication (DED1 – DED3) were used as measures of employee engagement. Trust_Mean, Commitment_Mean, and Engagement_Mean scores were obtained by averaging the relevant items. Demographic factors included gender, age, level of education, profession, and AI tool used. Some other variables in the original data set were not needed in the present study and so were not analysed, which meant that the analysis was kept focused on trust, engagement, and organisational commitment.

### *2.4 Data Preparation and Reliability*

Data were prepared using IBM SPSS Statistics 27. More than 450 valid cases were identified after initial screening for the main study variables. Cronbach's alpha was used to measure the reliability. The reliability of the measures was excellent, with α values being .945 for trust, .911 for organizational commitment, .911 for vigor, and .897 for dedication. The α for the combined six-item employee engagement scale was .811. Thus, all remaining items were part of the final composite measures.

### *2.5 Statistical Analysis*

The IBM SPSS Statistics 27 software was used for statistical analysis. Descriptive statistics were used to summarize the sample and the main study variables as a first step. To investigate relationships between trust and organizational commitment, employee engagement, and age, the data were analyzed using Pearson correlation analysis. Independent-samples t-tests were used to compare differences between gender means, and one-way ANOVAs were used to compare education, profession, and AI-tool means. To determine the relationship of trust, employee engagement, age, and gender with organizational commitment, multiple linear regression analysis was performed. Levene's test, variance inflation factors, Durbin-Watson statistics, residual plots, Cook's distance, and leverage values were used to assess statistical assumptions and model diagnostics. The level of statistical significance was set at $p < .05$.

## 3. Results

### *3.1 Sample Characteristics*

The female population made up 41.6% of the sample, and the male population 58.4%. As for qualifications, the most common was a postgraduate qualification, with 51.2%, followed by graduates with 27.0% and professional qualifications with 17.8%. High-school education was reported by 3.2% of respondents, while 0.8% reported another educational qualification. ChatGPT was the most commonly used AI tool, followed by image-generation AI tools, QuillBot, Google Gemini or other text-generative AI tools, and other AI tools. An implausible age value was treated as missing data, leaving 499 respondents with age data. The mean age was 34.00 years (SD = 10.62), with a range of 18–77 years as shown in Table 1.

**Table 1. Sample characteristics**

| Variable | Category | n | % |
|---|---|---|---|
| **Gender** | Female | 208 | 41.6 |
| | Male | 292 | 58.4 |
| **Education** | High school | 16 | 3.2 |
| | Graduate | 135 | 27.0 |
| | Postgraduate | 256 | 51.2 |
| | Professional qualification | 89 | 17.8 |
| | Other | 4 | 0.8 |
| **AI tool used** | ChatGPT | 219 | 43.8 |
| | QuillBot | 100 | 20.0 |
| | Image-generation AI tools | 116 | 23.2 |
| | Google Gemini/other text-generative AI | 54 | 10.8 |
| | Other AI tools | 11 | 2.2 |

### *3.2 Reliability and Descriptive Statistics*

Cronbach's alpha was used to determine the internal consistency. Table 2 shows that all scales had acceptable to excellent reliability. Overall, the highest level of reliability was for trust in generative AI ($\alpha$ = .945), and the measures of organizational commitment and vigor ($\alpha$ = .911) and dedication ($\alpha$ = .897) were also quite reliable. The composite measure of employee engagement also demonstrated good reliability ($\alpha$ = .811). Thus, all retained items were used to form the appropriate composite scores. The mean scores indicated generally high levels across the three main constructs. The means for trust in generative AI, organizational commitment, and employee engagement were 5.66 (SD = 1.01), 6.18 (SD = 0.75), and 5.90 (SD = 0.76), respectively.

**Table 2. Reliability of the study measures**

| Variable | Items | Cronbach's α |
|---|---|---|

| | | |
|---|---|---|
| Trust in GenAI | 4 | .945 |
| Organizational commitment | 5 | .911 |
| Vigor | 3 | .911 |
| Dedication | 3 | .897 |
| Employee engagement | 6 | .811 |

### *3.3 Correlations Among the Main Variables*

Pearson correlation analysis was used to explore correlations between trust in generative AI, organizational commitment, and employee engagement. All three constructs were significantly and positively correlated. Organizational commitment ($r = .371$, $p < .001$) and employee engagement ($r = .470$, $p < .001$) were positively correlated with trust. Organizational commitment was positively associated with employee engagement ($r = .406$, $p < .001$). The association between age and organizational commitment was very weak and positive ($r = .101$, $p = .024$). Its correlations with trust were not statistically significant, $r = .070$, $p = .116$, and with employee engagement, $r = .077$, $p = .085$. The results confirm the proposed positive links between trust and engagement, as well as between engagement and organizational commitment.

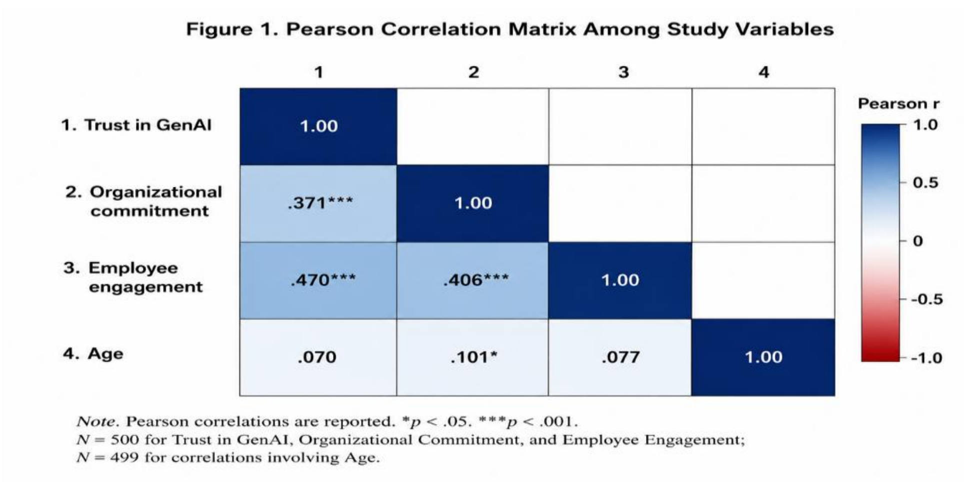


**Figure 1. Pearson correlations among study variables**

As shown in Figure 1, trust in generative AI was positively related to both organizational commitment and employee engagement. Employee engagement was also positively associated with organizational commitment. In contrast, age showed only weak relationships with the main study variables. Overall, trust and engagement appeared more closely connected with organizational attitudes than age.

### *3.4 Gender Differences*

Independent-samples t-tests were used to explore the differences in trust, organizational commitment, and employee engagement between genders. As presented in Table 3, no significant gender difference was found for trust, $t(498) = -1.162$, $p = .246$, or employee engagement, $t(498) = -1.288$, $p = .198$. Male respondents reported significantly higher organizational commitment ($M = 6.31$, $SD = 0.68$) than female respondents ($M = 6.00$, $SD = 0.81$), $t(498) = -4.719$, $p < .001$, Cohen's $d = 0.43$.

**Table 3. Independent-samples t-tests by gender**

| Outcome | Female | Male | t | p | Cohen's d |
|---|---|---|---|---|---|
| Trust | 5.60 (1.02) | 5.71 (1.00) | -1.162 | .246 | 0.11 |

| | | | | | |
|---|---|---|---|---|---|
| Organizational commitment | 6.00 (0.81) | 6.31 (0.68) | -4.719 | <.001 | 0.43 |
| Employee engagement | 5.85 (0.73) | 5.94 (0.78) | -1.288 | .198 | 0.12 |

### *3.5 Differences by Profession, AI Tool, and Education*

One-way ANOVAs were used to assess whether trust, organizational commitment, and employee engagement varied between professions, AI tools, and education categories. All analyses had Levene's test of homogeneity of variance that was non-significant, thus supporting the homogeneity of variance assumption. As shown in Table 4, profession was not significantly associated with differences in trust, $F(5,494) = 0.487$, $p = .786$; organizational commitment, $F(5,494) = 0.740$, $p = .594$; or engagement, $F(5,494) = 1.560$, $p = .170$. Similarly, no significant differences were identified across AI-tool categories for trust, $F(4,495) = 1.006$, $p = .404$; commitment, $F(4,495) = 1.325$, $p = .260$; or engagement, $F(4,495) = 1.817$, $p = .124$. Education groups also did not differ significantly on trust, $F(4,495) = 0.276$, $p = .893$; commitment, $F(4,495) = 0.342$, $p = .850$; or engagement, $F(4,495) = 0.703$, $p = .590$.

**Table 4. Summary of one-way ANOVA results**

| Grouping variable | Outcome | F | df | p |
|---|---|---|---|---|
| Profession | Trust | 0.487 | 5, 494 | .786 |
| | Commitment | 0.740 | 5, 494 | .594 |
| | Engagement | 1.560 | 5, 494 | .170 |
| AI tool | Trust | 1.006 | 4, 495 | .404 |
| | Commitment | 1.325 | 4, 495 | .260 |
| | Engagement | 1.817 | 4, 495 | .124 |
| Education | Trust | 0.276 | 4, 495 | .893 |
| | Commitment | 0.342 | 4, 495 | .850 |
| | Engagement | 0.703 | 4, 495 | .590 |

### *3.6 Multiple Regression Predicting Organizational Commitment*

To examine the association between trust in generative AI, employee engagement, age, gender, and organizational commitment, a multiple linear regression was conducted. The overall regression model proved to be statistically significant, $F(4,494) = 39.094$, $p < .001$. The model had an R2 of .240 and an adjusted R2 of .234, which means that the predictors accounted for around 24.0% of the variance in organizational commitment. As indicated in Table 5, the strongest significant predictor of organizational commitment was employee engagement ($\beta = .287$, $p < .001$). Trust in generative AI was also a significant positive predictor of organizational commitment ($\beta = .223$, $p < .001$). Gender was a statistically significant predictor ($\beta = .175$, $p < .001$), whereas age was not a significant predictor after controlling for the other variables ($\beta = .047$, $p = .233$). Regression diagnostics showed that the model was satisfactory. The Durbin–Watson statistic was 1.955, indicating no serious residual autocorrelation. There was no concern with multicollinearity because the VIF values were in the range of 1.011 to 1.288. Five cases had absolute standardized residuals greater than 3, but the maximum Cook's distance was .055 and the maximum leverage was .038, suggesting that these observations were not strongly influential. Therefore, all valid cases were retained.

**Table 5. Multiple regression predicting organizational commitment**

| Predictor | B | SE B | β | t | p | 95% CI for B |
|---|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| Constant | 3.021 | .262 | — | 11.533 | <.001 | [2.507, 3.536] |
| Trust in GenAI | .167 | .033 | .223 | 5.023 | <.001 | [.102, .232] |
| Employee engagement | .284 | .044 | .287 | 6.446 | <.001 | [.197, .370] |
| Age | .003 | .003 | .047 | 1.194 | .233 | [-.002, .009] |
| Gender | .268 | .060 | .175 | 4.443 | <.001 | [.149, .386] |

*Note.* $N = 499$. $R = .490$, $R^2 = .240$, adjusted $R^2 = .234$, $F(4, 494) = 39.094$, $p < .001$.

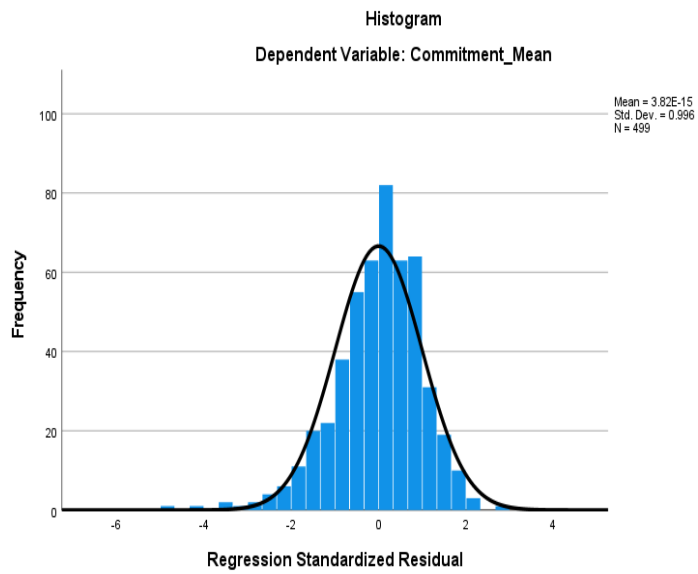


**Figure 2. Histogram of Standardized Regression Residuals for Organizational Commitment**

The histogram of standardized residuals for the organizational commitment regression model showed a normal distribution of the residuals as shown in Figure 2. The majority of the residuals were also located near zero and followed a roughly bell-shaped distribution with a good fit to the normal curve. There were a few observations in the lower tail, but their number was small. The average of the standardized residuals was near 0, and the standard deviation was near 1. Overall, the residual distribution was approximately normal, supporting the normality assumption for the multiple liner regression analysis.

## *3.7 Summary of Hypothesis Testing*

The findings overall confirmed the hypotheses related to the positive relationships between the key constructs. Organizational commitment and employee engagement were significantly and positively related to trust in generative AI, and employee engagement was significantly and positively related to organizational commitment. The regression analysis also revealed that trust and employee engagement made unique significant contributions to organizational commitment. Employee engagement emerged as the strongest predictor in the model. Profession, education, and AI-tool category did not produce significant differences in any of the three outcomes, whereas gender differences were significant only for organizational commitment. A summary of hypothesis testing is shown in Table 6.

**Table 6. Summary of Hypothesis Testing**

| Hypothesis | Relationship Tested | Statistical Result | Decision |
|---|---|---|---|

| | | | |
|---|---|---|---|
| H1 | Trust in generative AI is positively associated with organizational commitment. | $r = .371, p < .001$ | Supported |
| H2 | Trust in generative AI is positively associated with employee engagement. | $r = .470, p < .001$ | Supported |
| H3 | Employee engagement is positively associated with organizational commitment. | $r = .406, p < .001$ | Supported |
| H4 | Trust in generative AI and employee engagement significantly predict organizational commitment. | Trust: $\beta = .223$, $p < .001$; Engagement: $\beta = .287$, $p < .001$; Model: $F(4, 494) = 39.094$, $p < .001$, $R^2 = .240$ | Supported |

## 4. Discussion

The results suggest that trust in generative AI is positively related to employee engagement and organizational commitment. Those who expressed more trust in GenAI were more likely to report high levels of engagement and organizational commitment. Employee engagement had the strongest positive association with organizational commitment ($r = .406$), followed by trust in GenAI ($r = .371$). Trust in GenAI, employee engagement, age, and gender collectively explained 24% of the variance in organizational commitment. Age was not a significant predictor, whereas gender was statistically significant in the regression model. The differences among employees by profession, education, and type of AI tool were not statistically significant, indicating that attitudes toward these tools might be somewhat similar across employee subgroups. The results are relevant to companies that are adopting generative AI for use in their workplaces. Successful implementation of AI is not just a matter of adoption, but also about keeping employee trust and engagement, especially to ensure organizational commitment. Employees can build trust in adopting AI in their practices through transparent communication, engagement, proper training, and enabling human oversight.

The findings also indicate that engagement is a significant predictor of organizational commitment and will continue to be an important factor, especially when it comes to organizational commitment. The results, from a theoretical viewpoint, link technology-related trust and existing organizational attitudes, suggesting that employees' relationship with emerging technologies can become entangled in their overall relationship with the organization. The present results extend the previous research that has examined the relationship between employee attitudes and organizational commitment in general. Allen and Meyer (1990) showed that commitment is a psychological attachment to the organization, and that it is related to employees' experiences of the workplace. Meyer et al. (1993) also demonstrated that organizational commitment is a significant work attitude that is linked to employees' relationship with organizations and occupations. In the era of generative AI, the current finding that employee engagement is a strong predictor of organizational commitment adds to a well-documented view. The present study, however, extends their direct association and group difference findings and their multiple regression analysis, not by repeating their mediation model. Liu et al. (2025) also found that the use of generative AI can impact employee outcomes, such as commitment to the job in the context of career, noting that personal attitudes towards generative AI drive these outcomes. The role of trust in the present analysis is also consistent with the work of Lin et al. (2025), which showed that trust in generative AI impacts employee behavioural outcomes, except that the impact of trust can vary according to the innovation behaviour analyzed.

Together, these comparisons reveal that trust is a crucial (but situation-dependent) mechanism by which employees react to GenAI. The results should be interpreted with certain limitations. The study relied upon secondary cross-sectional data. The use of self-reported responses on questionnaires to assess all the principal variables may result in common-method and social-desirability bias. Relatively few respondents were in some demographic categories, which might have limited the power to identify differences between categories. Future research may employ a longitudinal or experimental design to assess the potential for causal relationships between the changes in trust in generative AI and changes in engagement and organizational commitment. Other organizational mechanisms that could be explored include perceptions of AI transparency, procedural fairness, privacy concerns, human oversight, leadership support, training quality, and employee involvement in the implementation of AI. Larger and more balanced groups would enable more robust comparisons between the professional, the educational, and the AI-use groups.

## 5. Conclusion

The research investigated the relationships between trust in generative AI, employee engagement, and organizational commitment. Results indicated that employee engagement and organizational commitment were both positively related to trust in generative AI. Employee engagement was positively correlated with organizational commitment and emerged as the strongest predictor in the regression model. The regression model explained 24% of the variance in organizational commitment; trust, employee engagement, and gender were significant predictors, whereas age was not. There were significant differences between genders only for organizational commitment, and no significant differences between professions or between categories of AI tools for major outcomes in the main study. Overall, the findings indicate that employees' attitudes toward generative AI are related to their attitudes toward work. Trust in AI and employee engagement, in particular, could play a crucial role in keeping employees loyal in increasingly AI-driven work environments. Further studies should employ a multi-source and a longitudinal research design and investigate other variables like transparency of AI, fairness, human supervision, privacy, leadership's support, and employee engagement in AI implementation.

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