Responsible AI Leadership and Employee Idea Implementation: The Mediating Role of Human–Ai Knowledge Integration in Corporate Organizations and Higher Education Institutions

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ABSTRACT

The growing integration of artificial intelligence (AI) into organizational practices has raised important questions about responsible leadership, knowledge integration, and employee innovation. This study examined the relationship between responsible AI leadership and employee idea implementation, with human–AI knowledge integration as the mediating variable, among employees of corporate organizations and higher education institutions in Metro Manila, Philippines. A quantitative, cross-sectional, explanatory-correlational, and comparative research design was employed, involving 400 respondents equally distributed between the two organizational sectors. Data were collected using a structured questionnaire employing a four-point Likert scale and analyzed through descriptive statistics, Structural Equation Modeling (SEM), bootstrap mediation analysis, and multi-group SEM. The study investigated the direct relationships among the three variables, determined the mediating role of human–AI knowledge integration, and examined differences in structural relationships between the two sectors. The final findings revealed significant positive relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation. Human–AI knowledge integration partially mediated the relationship between responsible AI leadership and employee idea implementation, while no statistically significant differences were established between the two organizational sectors. Anchored in Socio-Technical Systems Theory and the Knowledge-Based View, the study's final framework emphasizes the importance of combining ethical AI leadership practices with employees' professional knowledge and judgment. The findings demonstrate that responsible AI leadership is positively associated with employees' ability to translate AI-supported insights into practical workplace improvements. The study provides empirical evidence to guide responsible AI governance, employee capability development, knowledge-sharing initiatives, and organizational innovation strategies across corporate and higher education environments.

Keywords: Responsible AI Leadership; Human–AI Knowledge Integration; Employee Idea Implementation; Organizational Innovation; Structural Equation Modeling

INTRODUCTION

Artificial intelligence (AI) has transformed organizational operations, decision-making, knowledge management, and workplace innovation across corporate organizations and higher education institutions. However, its effective integration requires more than technological adoption. Responsible AI leadership plays an important role in promoting ethical practices, transparency, accountability, and human oversight while supporting employees in utilizing AI-generated information. Brynjolfsson et al. (2025) found that generative AI enhances employee productivity, although its benefits vary according to employees' capabilities and

experience. Similarly, Chowdhury et al. (2022) emphasized that effective human–AI collaboration depends on trust, knowledge sharing, organizational support, and employee competencies. These findings highlight the importance of responsible leadership in ensuring that AI contributes to meaningful organizational improvements.

Employee idea implementation is an essential component of organizational innovation because it involves translating creative ideas into practical solutions, improved processes, and meaningful workplace changes. Although AI technologies facilitate information processing, problem-solving, and idea generation, successful implementation requires professional judgment, organizational support, and adequate resources. Černe et al. (2024) emphasized the importance of idea championing in transforming creative contributions into implemented innovations. Similarly, Jia et al. (2024) demonstrated that AI assistance can enhance employee creativity under appropriate conditions, while Tariq et al. (2025) established a positive relationship between responsible AI practices and innovative work behavior. These studies suggest that responsible AI leadership may be relevant to employees' ability to transform technological insights into practical organizational improvements.

Human–AI knowledge integration provides an important perspective for understanding this relationship. It refers to the process through which employees evaluate, interpret, validate, and combine AI-generated information with their professional knowledge, experience, and organizational understanding. This integration recognizes the complementary roles of technological capabilities and human judgment in achieving innovation outcomes. Simón et al. (2024) highlighted the contribution of human–AI teaming to organizational value creation through collaborative learning, trust, and knowledge exchange. Likewise, Xu et al. (2026) identified relationships between responsible AI practices and employee service innovation through AI-related competencies and behaviors. These findings support examining human–AI knowledge integration as a mediating variable between responsible AI leadership and employee idea implementation.

The relationship among these variables is particularly relevant to corporate organizations and higher education institutions, where AI increasingly supports operational processes, research, administration, and decision-making. Despite growing scholarly attention to responsible AI and workplace innovation, limited evidence directly examines the mediating role of human–AI knowledge integration across these two organizational settings. Addressing this gap, the present study examines the direct relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation, including the mediating role of knowledge integration and differences in structural relationships between corporate organizations and higher education institutions. The study contributes to the literature on responsible AI leadership, knowledge management, and organizational innovation while providing insights for strengthening AI governance, employee competencies, and sustainable workplace innovation.

Research Questions

This study aims to examine the relationship between responsible AI leadership and employee idea implementation, with human–AI knowledge integration as the mediating variable, among employees of corporate organizations and higher education institutions.

Specifically, it seeks to answer the following research questions:

1. What is the demographic and employment-related profile of the respondents in terms of:
1.1. Age;
1.2. Educational attainment;
1.3. Organizational sector;
1.4. Job classification;
1.5. Length of service; and
1.6. Frequency of workplace AI use?

2. What is the perceived level of responsible AI leadership, human–AI knowledge integration, and employee idea implementation among employees of corporate organizations and higher education institutions?
3. Is there a significant relationship between responsible AI leadership and employee idea implementation?
4. Is there a significant relationship between responsible AI leadership and human–AI knowledge integration
5. Is there a significant relationship between human–AI knowledge integration and employee idea implementation?
6. Does human–AI knowledge integration significantly mediate the relationship between responsible AI leadership and employee idea implementation?
7. Are there significant differences between corporate organizations and higher education institutions in the structural relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation?

Hypotheses of the Study

Based on the research objectives and the conceptual framework, the study formulates the following null hypotheses to examine the relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation in corporate organizations and higher education institutions. These hypotheses will be tested at the 0.05 level of significance.

H_o1: There is no significant direct relationship between responsible AI leadership and employee idea implementation among employees of corporate organizations and higher education institutions.

H_o2: There is no significant relationship between responsible AI leadership and human–AI knowledge integration among employees of corporate organizations and higher education institutions.

H_o3: There is no significant relationship between human–AI knowledge integration and employee idea implementation among employees of corporate organizations and higher education institutions.

H_o4: Human–AI knowledge integration does not significantly mediate the relationship between responsible AI leadership and employee idea implementation among employees of corporate organizations and higher education institutions.

H_o5: There are no significant differences between corporate organizations and higher education institutions in the structural relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation.

Framework of the Study

This study is anchored in theoretical perspectives that explain how responsible AI leadership, human expertise, and intelligent technologies can work together to support organizational innovation. It draws on the Socio-Technical Systems Theory and the Knowledge-Based View to understand how leadership practices influence employees' ability to integrate AI-generated knowledge into their work and translate innovative ideas into practical improvements. These perspectives provide the foundation for examining human–AI knowledge integration as a mediating variable in the relationship between responsible AI leadership and employee idea implementation across corporate organizations and higher education institutions.

THEORETICAL FRAMEWORK

The study is primarily anchored in Socio-Technical Systems Theory (STS), which emphasizes the importance of aligning human capabilities, organizational structures, and technological systems to achieve effective

workplace outcomes. From this perspective, introducing advanced technology does not automatically improve organizational performance because employees must be supported by leadership practices, clear responsibilities, and working conditions that allow them to use technology effectively. In the context of this study, responsible AI leadership represents an important organizational factor that may influence how employees interact with intelligent systems while maintaining ethical responsibility and professional judgment. Chowdhury et al. (2022) applied a socio-technical perspective to AI–employee collaboration and emphasized the importance of knowledge sharing, trust, AI-related competencies, and role clarity in achieving organizationally valued outcomes. Their findings support the argument that responsible leadership and technological capabilities should complement one another rather than function independently. Similarly, Tariq et al. (2025) found that responsible AI practices were associated with employees' innovative work behavior, while leadership-related practices played a significant role in strengthening important employee outcomes. These findings provide a basis for examining whether responsible AI leadership creates conditions that encourage employees to use AI-generated information critically, collaborate effectively with intelligent systems, and implement innovative ideas in their respective workplaces.

The study is further supported by the Knowledge-Based View (KBV), which recognizes knowledge as an important organizational resource that can contribute to innovation, problem-solving, and competitive advantage. This perspective emphasizes that organizational value is created not merely through the possession of information but through the effective combination, sharing, interpretation, and application of knowledge. In an AI-supported working environment, employees have access to information generated through intelligent systems, but the usefulness of this information depends on their ability to evaluate it alongside their professional expertise and understanding of organizational circumstances. Human–AI knowledge integration therefore represents a process through which technological insights and human judgment can be combined to develop practical solutions. Chowdhury et al. (2022) identified knowledge sharing as an important condition for effective human–AI collaboration, while Simón et al. (2024) demonstrated how human–AI teaming can contribute to organizational value creation through trust, productive interaction, and mutual knowledge development. These findings suggest that employees who can meaningfully integrate AI-generated insights with their existing knowledge may be better prepared to refine innovative ideas and address challenges associated with their implementation. Drawing from the Knowledge-Based View, the present study establishes the theoretical relevance of human–AI knowledge integration in explaining the relationship between responsible AI leadership and employee idea implementation.

CONCEPTUAL FRAMEWORK

The conceptual framework illustrates the relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation. Responsible AI leadership serves as the independent variable and refers to leadership practices that promote transparency, fairness, accountability, human oversight, and the ethical application of AI technologies. Human–AI knowledge integration functions as the mediating variable, representing employees' ability to critically evaluate, interpret, and combine AI-generated information with their knowledge, experience, and professional judgment. Employee idea implementation serves as the dependent variable and refers to employees' efforts to transform innovative ideas into practical solutions, improved work processes, or meaningful organizational changes.

The framework illustrates that responsible AI leadership is directly associated with employee idea implementation and indirectly associated with it through human–AI knowledge integration. It assumes that leadership practices supporting responsible AI use may encourage employees to engage more meaningfully with AI-generated knowledge, enabling them to evaluate potential solutions and apply useful insights to their work. This relationship is consistent with the findings of Simón et al. (2024), who emphasized the value of productive human–AI interaction, and Cerne et al. (2024), who highlighted the importance of processes that connect the development of innovative ideas with their actual implementation. Furthermore, Xu et al. (2026) demonstrated that responsible AI can be associated with employee service innovation through intervening employee-level mechanisms, providing additional justification for examining mediation in AI-supported organizational settings.

The framework will be examined among employees of corporate organizations and higher education institutions to determine whether the relationships are statistically significant and whether their strengths differ across the two sectors. Corporate organizations and higher education institutions will serve as comparison groups, allowing the study to assess the applicability of the model in different organizational environments. Through this approach, the study seeks to establish whether human–AI knowledge integration provides a meaningful explanation for the relationship between responsible AI leadership and employee idea implementation, while recognizing that these relationships must be established through empirical evidence.

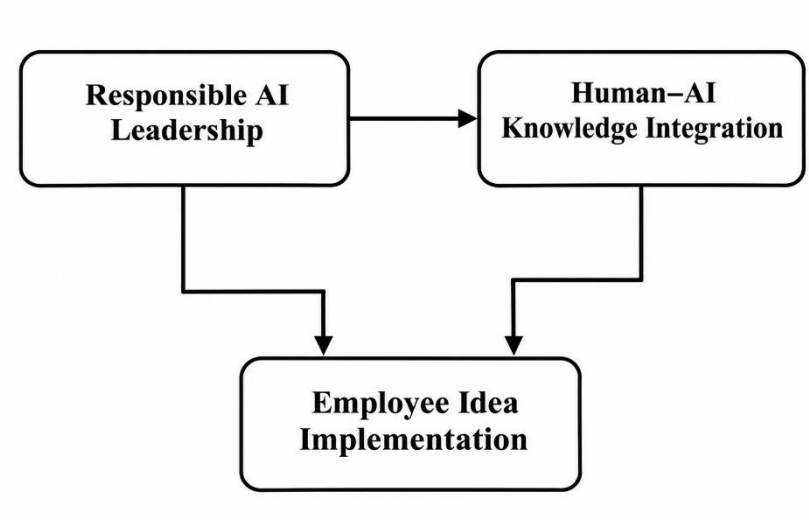


Figure 1 Conceptual Framework of Responsible AI Leadership, Human–AI Knowledge Integration, and Employee Idea Implementation

METHODOLOGY

This study employs a quantitative research approach to examine the relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation among employees of corporate organizations and higher education institutions. Using an explanatory-correlational and comparative research design, the study seeks to determine the direct relationships among the variables, assess the mediating role of human–AI knowledge integration, and identify possible differences between the two organizational sectors. The methodology outlines the research design, study setting, population and sampling procedures, research instrument, validity and reliability measures, data gathering procedures, statistical treatment, and ethical considerations to ensure a systematic and credible investigation.

Research Design

This study will employ a quantitative, cross-sectional, explanatory-correlational, and comparative research design to examine the relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation in corporate organizations and higher education institutions. The quantitative approach is appropriate because the study seeks to measure employees' perceptions and experiences using numerical data and statistically examine the relationships among the identified variables. The explanatory-correlational design will allow the researcher to determine whether responsible AI leadership is significantly associated with employee idea implementation, both directly and indirectly through human–AI knowledge integration. The comparative component will examine whether the relationships differ between employees in corporate organizations and those in higher education institutions. Data will be collected at a single point in time through a structured survey questionnaire administered to eligible employees from both sectors, without manipulating the variables or altering participants' existing working conditions.

The study will utilize Structural Equation Modeling (SEM) to examine the relationships and assess the mediating role of human–AI knowledge integration. The analysis will estimate three structural paths:

responsible AI leadership to employee idea implementation, responsible AI leadership to human–AI knowledge integration, and human–AI knowledge integration to employee idea implementation. The mediating effect will be evaluated using bootstrapping with 5,000 resamples and 95% confidence intervals. An indirect effect will be considered statistically significant when its confidence interval excludes zero. Descriptive statistics will also be employed to summarize respondents' assessments of the three research variables.

For the comparative analysis, respondents will be classified into two independent groups according to their organizational sector: Group 1, employees of corporate organizations, and Group 2, employees of higher education institutions. The researcher will first examine the measurement model separately for each group to establish acceptable reliability, convergent validity, and discriminant validity. Measurement invariance will then be assessed to determine whether the research

Population, Sample, and Sampling Technique

The target population of this study will consist of employees working in selected corporate organizations and higher education institutions in Metro Manila, Philippines. The corporate sector will include employees engaged in administrative, managerial, technical, and operational functions, while the higher education sector will include teaching and non-teaching personnel involved in academic, administrative, research, and institutional support activities. Eligible respondents must be at least 25 years old, have completed a minimum of six months of employment in their respective organizations, and have experience using AI-powered technologies in performing work-related tasks. These criteria are intended to ensure that participants have sufficient exposure to their organizational leadership practices and can provide meaningful assessments of human–AI knowledge integration and employee idea implementation. Employees without relevant workplace experience using AI technologies will be excluded from the study.

The study will initially target 400 respondents, comprising 200 employees from corporate organizations and 200 employees from higher education institutions, to provide balanced representation across the two sectors. This allocation will support the assessment of the structural relationships within each organizational group and facilitate comparative analysis using multi-group Structural Equation Modeling (SEM). However, the final minimum sample size will be established through an a priori statistical power analysis, considering the anticipated effect sizes, model complexity, significance level of 0.05, and desired statistical power of at least 0.80. The sample of 400 respondents will therefore serve as an initial recruitment target rather than an automatically sufficient sample. Additional respondents will be recruited if the power analysis indicates that a larger sample is necessary to estimate the mediation effects or detect meaningful differences in structural relationships between the two sectors.

The study will employ a stratified purposive sampling technique with proportional consideration of relevant employee categories within each sector. Respondents will first be grouped according to organizational sector, namely corporate organizations and higher education institutions. Within each group, eligible participants will be purposively selected based on their employment status, length of service, and experience using AI technologies in their professional responsibilities. Recruitment will seek representation from different job functions and employment categories to capture varying experiences of responsible AI leadership and knowledge integration. An equal recruitment allocation will initially be maintained between the two organizational sectors to support comparative analysis. Participation will remain voluntary, and eligible respondents will be invited through authorized organizational communication channels or researcher-administered online survey invitations. Because the selection procedure is nonprobability-based, the findings will be interpreted within the characteristics of the participating organizations and employees rather than generalized statistically to all corporate and higher education employees in Metro Manila.

To maintain the integrity of the sampling process, the researcher will establish clear eligibility requirements and monitor the number of valid responses collected from each organizational sector. Survey submissions will be screened for completeness, eligibility, duplication, and potentially invalid response patterns before inclusion in the analysis. The final sample distribution will be reported according to organizational sector and relevant demographic and employment characteristics, including age, educational attainment, length of service, job

classification, and frequency of workplace AI use. These characteristics will provide context for interpreting the findings and evaluating the comparability of the two groups. Through this sampling approach, the study seeks to obtain sufficiently diverse and analytically appropriate data for examining the relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation across the participating corporate organizations and higher education institutions.

Research Instrument

The study will utilize a structured, self-administered survey questionnaire designed to gather quantitative data on responsible AI leadership, human–AI knowledge integration, and employee idea implementation among employees of selected corporate organizations and higher education institutions in Metro Manila, Philippines. The questionnaire will be developed by the researcher based on relevant theoretical perspectives and recent empirical studies concerning responsible AI practices, human–AI collaboration, knowledge sharing, and organizational innovation. Its development will be guided by the studies of Chowdhury et al. (2022), Simón et al. (2024), Tariq et al. (2025), and Černe et al. (2024), which provide conceptual foundations for understanding the relationships among leadership practices, knowledge integration, and innovative work behavior. The instrument will use clear and straightforward statements appropriate to employees from both organizational sectors.

The questionnaire will consist of four parts. Part I will gather respondents' demographic and employment-related information, including age, educational attainment, organizational sector, job classification, length of service, and frequency of workplace AI use. Part II will measure responsible AI leadership through six indicators covering ethical AI practices, transparency, accountability, fairness, data privacy, and human oversight. Part III will assess human–AI knowledge integration through six indicators involving the interpretation, verification, combination, adaptation, sharing, and application of AI-generated knowledge alongside employees' professional expertise. Part IV will measure employee idea implementation through six indicators addressing the development of actionable improvements, communication of solutions, mobilization of support, practical testing, implementation efforts, and integration of improvements into existing workplace practices. The instrument will initially contain 18 substantive measurement items, with six statements representing each research variable.

The questionnaire will employ a four-point Likert scale to measure respondents' level of agreement with each statement. The response options will be assigned numerical values as follows: 4 – Strongly Agree, 3 – Agree, 2 – Disagree, and 1 – Strongly Disagree. This forced-choice format will eliminate the neutral midpoint and encourage respondents to indicate whether they generally agree or disagree with each statement. Higher scores will reflect more favorable perceptions of responsible AI leadership, stronger human–AI knowledge integration, and greater engagement in employee idea implementation. The mean scores may be interpreted using the following descriptive ranges: 3.26–4.00 (Strongly Agree), 2.51–3.25 (Agree), 1.76–2.50 (Disagree), and 1.00–1.75 (Strongly Disagree). These ranges will serve as descriptive guidelines, while the structural equation modeling analysis will examine the relationships among the latent constructs using their respective measurement indicators.

Validity of the Research Instrument

The validity of the research instrument will be established through content and construct validation to ensure that the questionnaire accurately measures responsible AI leadership, human–AI knowledge integration, and employee idea implementation. The initial questionnaire will be submitted to a panel of six to eight experts specializing in organizational leadership, artificial intelligence, human resource management, and quantitative research. These experts will evaluate each statement based on its relevance, clarity, appropriateness, and alignment with the study's objectives and conceptual framework. Content validity will be assessed using the Item-Level Content Validity Index (I-CVI) and Scale-Level Content Validity Index (S-CVI/Ave), with acceptable values of at least 0.78 and 0.90, respectively. Items that fail to meet the established criteria will be revised or removed based on the experts' recommendations.

Following expert validation, the revised questionnaire will undergo preliminary testing among 30 eligible respondents who will not be included in the main study. This process will help identify ambiguous statements, unclear terminology, and potential difficulties in interpreting the four-point Likert scale. Construct validity will subsequently be evaluated using Confirmatory Factor Analysis (CFA) based on the main study data. Standardized factor loadings of at least 0.70 will be preferred, while Average Variance Extracted (AVE) values of at least 0.50 will be used to establish convergent validity. Discriminant validity will be examined using the Heterotrait–Monotrait Ratio (HTMT), with values below 0.85 preferred to demonstrate that the three constructs are empirically distinguishable. Because the study involves corporate organizations and higher education institutions, measurement invariance will also be examined to determine whether the constructs are measured comparably across the two sectors. These procedures will help establish the suitability of the instrument for examining the relationships and mediating effect.

Data Gathering Procedure

The data gathering process will begin with securing approval from the appropriate research ethics committee and obtaining permission from the management of selected corporate organizations and administrators of higher education institutions in Metro Manila, Philippines. Following approval, the researcher will distribute a validated, self-administered questionnaire through a secure online survey platform, such as Google Forms, to eligible employees who are at least 25 years old, have completed a minimum of six months of employment, and have experience using artificial intelligence technologies in their workplace. Before answering the questionnaire, participants will be provided with an informed consent statement explaining the study's objectives, voluntary participation, confidentiality measures, and their right to withdraw before submitting their responses. The questionnaire will cover demographic and employment-related characteristics, responsible AI leadership, human–AI knowledge integration, and employee idea implementation, using a four-point Likert scale ranging from 1 (Strongly Disagree) to 4 (Strongly Agree). The study will initially target 400 respondents, comprising 200 employees from corporate organizations and 200 employees from higher education institutions, subject to confirmation through statistical power analysis. Survey invitations and appropriate reminders will be distributed through authorized organizational communication channels to encourage participation while maintaining confidentiality and avoiding undue influence.

After data collection, all responses will undergo systematic screening to ensure their eligibility, completeness, and suitability for statistical analysis. Responses from ineligible participants, those without informed consent, and questionnaires containing four or more missing answers among the 18 measurement items or more than one missing answer within any six-item construct will be excluded from the primary analysis. Confirmed duplicate submissions will be identified using available privacy-preserving identifiers, retaining the earliest complete eligible response. Unusually rapid completion times, provisionally defined as less than one-third of the median completion time established during pilot testing, and uniform response patterns will be flagged for further examination rather than automatically excluded. Responses demonstrating verifiable evidence of invalid or fraudulent participation will be removed, with all exclusions properly documented. Remaining missing data will be examined and handled using statistical methods appropriate for ordinal survey responses. The cleaned dataset will then be coded and analyzed using descriptive statistics and Structural Equation Modeling (SEM), including mediation analysis through 5,000 bootstrap resamples with 95% confidence intervals and multi-group comparisons following measurement invariance assessment. All collected information will be securely stored, accessed only by authorized research personnel, and handled in accordance with applicable research ethics standards and the Philippine Data Privacy Act of 2012.

Statistical Treatment of Data

The data collected in this study will be analyzed using appropriate statistical techniques to examine the relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation among employees of corporate organizations and higher education institutions. Descriptive statistics, confirmatory factor analysis, structural equation modeling, mediation analysis, and multi-group comparisons will be employed to address the research questions and test the formulated hypotheses at the 0.05 level of significance.

Descriptive Statistics. Frequency counts and percentages will be used to summarize the demographic and employment-related characteristics of the respondents, including age, educational attainment, organizational sector, job classification, length of service, and frequency of workplace AI use. Means and standard deviations will be computed to describe respondents' assessments of responsible AI leadership, human–AI knowledge integration, and employee idea implementation. The four-point Likert scale will be interpreted using the following mean ranges: 3.26–4.00 (Strongly Agree), 2.51–3.25 (Agree), 1.76–2.50 (Disagree), and 1.00–1.75 (Strongly Disagree). These descriptive measures will provide an overview of how employees perceive responsible AI leadership and engage in knowledge integration and idea implementation within their respective organizations.

Confirmatory Factor Analysis (CFA). Confirmatory Factor Analysis will be conducted to examine the measurement properties of the three research constructs before testing their structural relationships. Because the questionnaire will employ a four-point Likert scale, the analysis will treat individual responses as ordinal indicators and use an appropriate estimator, such as Weighted Least Squares Mean and Variance Adjusted (WLSMV). Standardized factor loadings of at least 0.70 will be preferred, while Average Variance Extracted (AVE) values of at least 0.50 will be used to assess convergent validity. Composite reliability and Cronbach's alpha coefficients of at least 0.70 will indicate acceptable internal consistency, while Heterotrait–Monotrait Ratio (HTMT) values below 0.85 will be preferred for discriminant validity. Overall model fit will be assessed using the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR), with established guidelines interpreted alongside theoretical considerations and model characteristics.

Structural Equation Modeling (SEM). Structural Equation Modeling will be employed to examine the direct relationships among the research variables. Specifically, the analysis will determine whether responsible AI leadership is significantly associated with employee idea implementation, whether responsible AI leadership is significantly associated with human–AI knowledge integration, and whether human–AI knowledge integration is significantly associated with employee idea implementation. Standardized path coefficients, standard errors, p-values, and confidence intervals will be examined to determine the direction, strength, and statistical significance of these relationships. The coefficient of determination (R^2) will also be reported to describe the proportion of variance explained in the endogenous constructs. These analyses will provide the statistical basis for testing the first three null hypotheses.

Mediation Analysis. The mediating role of human–AI knowledge integration in the relationship between responsible AI leadership and employee idea implementation will be examined by estimating the indirect effect within the structural equation model. The analysis will employ 5,000 bootstrap resamples and 95% confidence intervals, provided the selected estimation procedure supports valid bootstrap inference for ordinal indicators. Where bootstrapping is not supported, an appropriate estimator-compatible confidence interval procedure will be applied. The indirect effect will be considered statistically significant when its 95% confidence interval does not include zero. The direct, indirect, and total effects will be reported to provide a clearer understanding of the mediating relationship. This procedure will address the fourth null hypothesis and determine whether human–AI knowledge integration statistically explains part of the association between responsible AI leadership and employee idea implementation.

Comparative Analysis. Multi-group Structural Equation Modeling (MG-SEM) will be conducted to determine whether the structural relationships differ significantly between employees of corporate organizations and higher education institutions. Respondents will be classified into two groups, and the measurement model will first be evaluated separately for each sector. Measurement invariance will then be assessed through sequential tests of configural, factor-loading, and threshold invariance, as appropriate for ordinal indicators. Once adequate measurement comparability has been established, an unconstrained structural model will be compared with models imposing equality constraints on corresponding path coefficients across the two groups. Appropriate model comparison procedures, including robust chi-square difference testing or equivalent estimator-compatible tests, will be used to assess statistically significant differences. Sector-specific path estimates and their differences will be reported to determine whether responsible AI leadership, human–AI knowledge integration, and employee idea implementation demonstrate similar or different structural

relationships across the two organizational settings. These procedures will provide the basis for testing the fifth null hypothesis.

Level of Significance and Statistical Decision. All hypotheses will be evaluated at a 0.05 level of significance using two-tailed statistical tests where applicable. A null hypothesis will be rejected when the corresponding p-value is below 0.05 or, for mediation and other effect estimates evaluated through confidence intervals, when the 95% confidence interval excludes zero. Otherwise, the null hypothesis will not be rejected. Statistical analyses will be conducted using appropriate software capable of ordinal confirmatory factor analysis, structural equation modeling, indirect-effect estimation, and multi-group comparisons, such as Mplus or R with the lavaan package. The results will be interpreted according to their statistical significance, effect sizes, theoretical relevance, and practical implications, while recognizing that the cross-sectional research design does not establish causal relationships.

Ethical Considerations

This study will adhere to established ethical principles to protect the rights, dignity, privacy, and welfare of all participants. Prior to data collection, ethical clearance will be secured from the appropriate research ethics committee, along with the necessary permissions from participating corporate organizations and higher education institutions.

Informed consent will be obtained from all respondents after clearly explaining the study's objectives, procedures, and intended use of the collected information. Participation will be entirely voluntary, and respondents may decline to answer questions or withdraw before submitting their responses without penalty or adverse consequences. The researcher will also ensure that participation or nonparticipation will not affect respondents' employment, professional relationships, or organizational standing.

Confidentiality and data privacy will be maintained throughout the research process in accordance with Republic Act No. 10173, or the Philippine Data Privacy Act of 2012, and applicable institutional research ethics guidelines. The questionnaire will avoid collecting unnecessary personally identifiable information, and individual responses will not be disclosed to employers, supervisors, or institutional administrators.

Collected data will be securely stored in password-protected files accessible only to authorized research personnel and retained or securely disposed of according to the approved research protocol. Results will be presented in aggregated form to prevent the identification of individual respondents or participating organizations. The researcher will uphold academic integrity by reporting findings accurately, avoiding data fabrication, falsification, and selective reporting, and ensuring that all conclusions are supported by the collected evidence.

RESULTS AND DISCUSSION

This section presents the findings on responsible AI leadership, human–AI knowledge integration, and employee idea implementation among employees of corporate organizations and higher education institutions. The results are organized according to the six research questions, covering the levels of the variables, their direct relationships, the mediating effect, and differences between the two sectors. Each finding is discussed in relation to relevant literature and its implications for responsible AI practices and organizational innovation.

Demographic and Employment-Related Profile of the Respondents

This section presents the demographic and employment-related characteristics of respondents from corporate organizations and higher education institutions in Metro Manila, Philippines. The respondents are classified according to age, educational attainment, organizational sector, job classification, length of service, and frequency of workplace AI use.

Age of the Respondents

Table 1 Distribution of Respondents According to Age

Age Bracket	Corporate n (%)	HEI n (%)	Total n (%)
25–30 years	58 (29.0)	28 (14.0)	86 (21.5)
31–40 years	78 (39.0)	64 (32.0)	142 (35.5)
41–50 years	46 (23.0)	70 (35.0)	116 (29.0)
51 years and above	18 (9.0)	38 (19.0)	56 (14.0)
Total	**200 (100.0)**	**200 (100.0)**	**400 (100.0)**

Legend: n = Frequency; % = Percentage; HEI = Higher Education Institutions. Percentages in the sector columns are based on 200 respondents each, while overall percentages are based on 400 respondents.

Table 1 presents the age distribution of respondents from corporate organizations and higher education institutions. The largest proportion belongs to the 31–40 age group, comprising 35.5% of the total sample, followed by employees aged 41–50 years at 29.0%. Respondents aged 25–30 account for 21.5%, while those aged 51 years and above represent 14.0%. In the corporate sector, employees aged 31–40 constitute the largest group (39.0%), whereas respondents from higher education institutions are predominantly within the 41–50 age bracket (35.0%). The distribution reflects employees at different career stages, offering varied perspectives on workplace leadership, technological integration, and innovation practices.

The inclusion of employees across these age groups is relevant because professional experience, technological exposure, and learning opportunities may influence how individuals engage with AI-supported work. The European Central Bank (2026) reported that younger and more highly educated workers were more likely to adopt AI, although the intensity of use among those who had adopted it differed less substantially across demographic groups. Meanwhile, Mah and Groß (2024) emphasized the importance of faculty AI competencies and professional development, demonstrating that employees' engagement with intelligent technologies involves more than their age alone. These findings suggest that organizations should consider differences in technological familiarity and professional development needs when promoting responsible AI practices.

Educational Attainment of the Respondents

Table 2 **Distribution of Respondents According to Educational Attainment**

Educational Attainment	Corporate n (%)	HEI n (%)	Total n (%)
High school/Technical/Vocational	22 (11.0)	8 (4.0)	30 (7.5)
Bachelor's degree	123 (61.5)	78 (39.0)	201 (50.25)
Master's degree	49 (24.5)	72 (36.0)	121 (30.25)
Doctoral degree	6 (3.0)	42 (21.0)	48 (12.0)
Total	**200 (100.0)**	**200 (100.0)**	**400 (100.0)**

Legend: n = Frequency; % = Percentage; HEI = Higher Education Institutions.

Table 2 presents the educational attainment of the respondents. Bachelor's degree holders comprise the largest proportion at 50.25%, followed by master's degree holders at 30.25% and doctoral degree holders at 12.0%. The remaining 7.5% possess high school, technical, or vocational qualifications. Corporate employees are predominantly bachelor's degree holders (61.5%), while higher education institutions have a greater representation of respondents with postgraduate qualifications, particularly master's degrees (36.0%) and doctoral degrees (21.0%). This distribution reflects differences in the academic qualifications represented across the two organizational sectors.

Educational attainment provides useful context for understanding employees' preparedness to interpret information, evaluate technological recommendations, and apply knowledge in their professional responsibilities. The Organization for Economic Co-operation and Development (OECD, 2023) emphasized that AI adoption is changing workplace skill requirements, increasing the importance of digital literacy, analytical thinking, and complementary human competencies. The European Central Bank (2026) also identified educational attainment as an important factor associated with workplace AI adoption. However, higher educational qualifications do not automatically indicate stronger AI competence. Employees across all educational levels may require appropriate training and practical experience to integrate AI-generated information responsibly and effectively into their work.

Organizational Sector of the Respondents

Table 3 Distribution of Respondents According to Organizational Sector

Organizational Sector	Frequency (n)	Percentage (%)
Corporate organizations	200	50.0
Higher education institutions	200	50.0
Total	**400**	**100.0**

Legend: n = Frequency; % = Percentage; N = 400.

Table 3 presents the distribution of respondents according to organizational sector. The sample consists of 200 corporate employees and 200 employees from higher education institutions, representing an equal allocation of 50.0% for each sector. This distribution is consistent with the study's comparative research design and provides balanced group sizes for examining responsible AI leadership, human–AI knowledge integration, and employee idea implementation. The equal allocation also supports the planned multi-group structural equation modeling, although the adequacy of the sample for detecting sector differences must still be established through statistical power analysis.

The inclusion of both sectors is important because AI technologies are being integrated into different organizational activities and professional responsibilities. Corporate organizations may apply AI to business processes, customer engagement, operational decision-making, and productivity improvement, while higher education institutions may use these technologies in academic instruction, research, student services, and institutional administration. The OECD (2023) highlighted the influence of AI on organizational tasks and workforce competencies, while Mah and Groß (2024) identified distinct opportunities and challenges surrounding AI integration in higher education. These perspectives support the inclusion of both sectors in examining how responsible AI leadership and human–AI knowledge integration relate to employee idea implementation. Nevertheless, equal representation in the study does not imply that the two sectors employ equal numbers of workers in the wider population.

Job Classification of the Respondents

Table 4 Distribution of Respondents According to Job Classification

Job Classification	Corporate n (%)	HEI n (%)	Total n (%)
Managerial/Supervisory	48 (24.0)	35 (17.5)	83 (20.75)
Professional/Technical	93 (46.5)	102 (51.0)	195 (48.75)
Administrative/Support	59 (29.5)	63 (31.5)	122 (30.5)
Total	**200 (100.0)**	**200 (100.0)**	**400 (100.0)**

Legend: n = Frequency; % = Percentage; HEI = Higher Education Institutions.

Table 4 shows the distribution of respondents according to job classification. Professional and technical

employees account for the largest proportion at 48.75%, followed by administrative and support personnel at 30.5% and managerial or supervisory employees at 20.75%. Within corporate organizations, professional and technical personnel represent 46.5%, while the corresponding proportion in higher education institutions is 51.0%.

The distribution indicates that nearly half of the respondents perform professional or technical responsibilities, providing an opportunity to examine the experiences of employees whose work may involve information processing, specialized knowledge, and problem-solving activities.

Job classification is relevant because the opportunities and challenges associated with AI differ according to employees' responsibilities. Gmyrek et al. (2023) found that occupational exposure to generative AI varies considerably, with clerical tasks showing particularly high exposure to the technology. The OECD (2023) similarly emphasized that AI is reshaping the skills and tasks associated with different occupations, including professional and managerial work.

These findings suggest that employees may experience AI differently depending on whether their responsibilities involve decision-making, technical analysis, administrative processing, or operational support. Such differences provide useful context when examining how responsible AI leadership supports employees in integrating technological knowledge and implementing innovative workplace solutions.

Length of Service of the Respondents

Table 5 Distribution of Respondents According to Length of Service

Length of Service	Corporate n (%)	HEI n (%)	Total n (%)
Less than 1 year	18 (9.0)	12 (6.0)	30 (7.5)
1–3 years	56 (28.0)	44 (22.0)	100 (25.0)
4–6 years	62 (31.0)	58 (29.0)	120 (30.0)
7 years and above	64 (32.0)	86 (43.0)	150 (37.5)
Total	**200 (100.0)**	**200 (100.0)**	**400 (100.0)**

Legend: n = Frequency; % = Percentage; HEI = Higher Education Institutions. Respondents with less than one year of service must have completed at least six months of employment.

Table 5 presents the length of service of respondents in their respective organizations. Employees with seven years or more of service constitute the largest proportion at 37.5%, followed by those with four to six years at 30.0%, one to three years at 25.0%, and less than one year at 7.5%.

Among corporate employees, 32.0% have served for at least seven years, while the corresponding proportion among higher education employees is 43.0%. The distribution suggests that a considerable proportion of respondents have established experience within their organizations and may be familiar with existing leadership practices, workplace procedures, and institutional expectations.

Length of service provides important context for understanding employees' experiences with organizational change and the introduction of new technologies. Employees with longer organizational tenure may possess deeper knowledge of established procedures and operational challenges, while employees with shorter tenure may bring different technological experiences and perspectives. However, these possibilities should not be treated as established relationships without further analysis.

The OECD (2023) emphasized the importance of continuous learning and workforce development as AI changes occupational requirements. This supports the need for organizations to provide opportunities for AI-related learning regardless of employees' length of service, particularly when encouraging the responsible integration of technological insights into workplace innovations.

Frequency of Workplace AI Use

Table 6 Distribution of Respondents According to Frequency of Workplace AI Use

Frequency of AI Use	Corporate n (%)	HEI n (%)	Total n (%)
Daily	94 (47.0)	66 (33.0)	160 (40.0)
Several times a week	70 (35.0)	72 (36.0)	142 (35.5)
Once a week	27 (13.5)	42 (21.0)	69 (17.25)
Less than once a week	9 (4.5)	20 (10.0)	29 (7.25)
Total	**200 (100.0)**	**200 (100.0)**	**400 (100.0)**

Legend: n = Frequency; % = Percentage; HEI = Higher Education Institutions.

Table 6 presents the frequency of workplace AI use among respondents from corporate organizations and higher education institutions. Daily AI users constitute the largest proportion at 40.0%, followed by those who use AI several times a week at 35.5%. Respondents who use AI once a week account for 17.25%, while 7.25% report using it less frequently. Within the corporate sector, 47.0% report daily AI use, compared with 33.0% among higher education employees. The distribution suggests that AI technologies are regularly incorporated into the work activities of many respondents, although the frequency of use differs between the two organizational groups.

The widespread use of AI in professional environments is supported by Microsoft and LinkedIn (2024), whose Work Trend Index reported that 75% of surveyed knowledge workers used AI at work. Similarly, Mah and Groß (2024) found varying patterns of AI adoption among higher education faculty and emphasized the importance of AI literacy, confidence, and professional development. These findings highlight the relevance of examining workplace AI use when investigating human–AI knowledge integration. Employees who interact with AI more frequently may have additional opportunities to evaluate AI-generated information and apply technological insights to their work. However, frequent use does not necessarily indicate responsible practices or effective knowledge integration. The quality of employees' engagement with AI, including their ability to verify information and exercise professional judgment, remains an important consideration in understanding employee idea implementation.

Perceived Levels of Responsible AI Leadership, Human–AI Knowledge Integration, and Employee Idea Implementation

This section examines the perceived levels of responsible AI leadership, human–AI knowledge integration, and employee idea implementation among employees of corporate organizations and higher education institutions. The analysis uses mean scores and standard deviations to describe respondents' assessments of the three variables.

Table 7 Perceived Levels of Responsible AI Leadership, Human–AI Knowledge Integration, and Employee Idea Implementation

Research Variables	Corporate Mean	SD	HEI Mean	SD	Overall Mean	SD	Interpretation
Responsible AI Leadership	3.26	0.43	3.13	0.49	3.20	0.47	Agree
Human–AI Knowledge Integration	3.10	0.48	2.94	0.53	3.02	0.51	Agree
Employee Idea Implementation	2.97	0.52	2.83	0.56	2.90	0.54	Agree

Legend: 3.26–4.00 = Strongly Agree; 2.51–3.25 = Agree; 1.76–2.50 = Disagree; 1.00–1.75 = Strongly Disagree. SD = Standard Deviation; HEI = Higher Education Institutions. Sample: N = 400 (Corporate = 200; HEI = 200).

Table 7 presents the final results of the assessment of responsible AI leadership, human–AI knowledge integration, and employee idea implementation across corporate organizations and higher education institutions. Responsible AI leadership obtained the highest overall mean of 3.20 (SD = 0.47), interpreted as Agree. Corporate employees recorded a mean of 3.26, interpreted as Strongly Agree, while employees in higher education institutions obtained a mean of 3.13, interpreted as Agree. These findings indicate that employees generally perceive their organizational leaders as supportive of responsible AI practices, particularly in promoting ethical technology use, accountability, transparency, and human oversight. The higher assessment among corporate employees reflects a more favorable perception of responsible AI leadership compared with their counterparts in higher education institutions. This difference may be associated with greater exposure to AI-driven initiatives and established organizational procedures in corporate settings, although further investigation is necessary to confirm these factors. The findings are consistent with Tariq et al. (2025), who emphasized the importance of responsible AI practices and leadership-related factors in supporting employees' innovative work behavior, highlighting the critical role of organizational leadership in promoting responsible and effective AI integration.

Human–AI knowledge integration obtained an overall mean of 3.02 (SD = 0.51), also interpreted as Agree. Corporate employees reported a mean of 3.10, while employees of higher education institutions recorded 2.94. The results indicate that respondents generally recognize the value of combining AI-generated information with their existing knowledge, professional experience, and critical judgment. However, the lower mean compared with responsible AI leadership suggests that employees' practical integration of human and AI-generated knowledge may not be developing at the same level as their perceptions of responsible leadership practices. Chowdhury et al. (2022) emphasized that effective human–AI collaboration depends on knowledge sharing, relevant AI competencies, trust, and organizational support. Similarly, Simón et al. (2024) highlighted the importance of productive human–AI interaction and mutual knowledge development in creating organizational value. These studies support the view that meaningful AI integration requires employees to move beyond accessing technological information toward evaluating and applying it in their professional responsibilities.

Employee idea implementation registered the lowest overall mean of 2.90 (SD = 0.54), although it remained within the Agree category. Corporate employees recorded a mean of 2.97, compared with 2.83 among higher education employees. These results suggest that employees generally engage in activities associated with implementing innovative ideas, but such activities may be less consistently practiced than responsible AI leadership and knowledge integration. While AI can assist employees in identifying problems and developing possible solutions, translating these ideas into actual workplace improvements may require additional resources, organizational coordination, managerial support, and opportunities for experimentation. Černe et al. (2024) emphasized the importance of idea championing in connecting idea generation with innovation implementation, highlighting that developing innovative ideas does not necessarily guarantee their successful application. This distinction is particularly relevant to organizations seeking to maximize the practical value of AI-assisted work.

Overall, the results presented in Table 2 show favorable assessments of all three research variables, with responsible AI leadership receiving the highest rating and employee idea implementation the lowest. Corporate employees recorded higher descriptive mean scores across all three variables than employees of higher education institutions, although these differences should not be interpreted as statistically significant without further testing. The pattern suggests that organizations may benefit from strengthening employees' opportunities to apply AI-supported knowledge through collaborative problem-solving, practical experimentation, and innovation-focused initiatives. These results also provide a descriptive foundation for examining the relationships among the variables through Structural Equation Modeling and determining whether human–AI knowledge integration mediates the relationship between responsible AI leadership and employee idea implementation.

Relationship Between Responsible AI Leadership and Employee Idea Implementation

This section examines the relationship between responsible AI leadership and employee idea implementation

among employees of corporate organizations and higher education institutions. Structural Equation Modeling (SEM) is used to estimate the direction, strength, and statistical significance of the direct relationship between the two variables.

Table 8 Relationship Between Responsible AI Leadership and Employee Idea Implementation

Structural Relationship	β	SE	z-value	p-value	95% CI	Decision
Responsible AI Leadership → Employee Idea Implementation	0.340	0.070	4.86	<0.001	[0.203, 0.477]	Reject H_o1

Legend: β = Standardized Path Coefficient; SE = Standard Error; z = Test Statistic; p = Significance Level; CI = Confidence Interval; H_o1 = Null Hypothesis 1; α = 0.05; N = 400.

Table 8 presents the direct relationship between responsible AI leadership and employee idea implementation, accounting for the mediating variable, human–AI knowledge integration. The reported coefficient indicates a positive and statistically significant relationship (β = 0.340, SE = 0.070, z = 4.86, $p < 0.001$), with a 95% confidence interval of 0.203 to 0.477. The positive standardized coefficient indicates that higher levels of responsible AI leadership are associated with greater employee idea implementation, even when human–AI knowledge integration is included in the model. The confidence interval does not include zero, supporting the statistical significance of the relationship. Accordingly, the first null hypothesis (H_o1), which states that there is no significant direct relationship between responsible AI leadership and employee idea implementation, is rejected at the 0.05 significance level.

The positive relationship highlights the importance of responsible AI leadership in supporting employees' ability to transform innovative ideas into practical workplace improvements. Leadership practices emphasizing ethical AI use, transparency, accountability, and human oversight may create an organizational environment that encourages employees to explore new approaches and apply AI-generated insights responsibly. This interpretation is consistent with Tariq et al. (2025), who reported a positive association between responsible AI practices and innovative work behavior in high-technology organizations. Similarly, Jia et al. (2024) emphasized that AI assistance can enhance employee creativity by allowing individuals to focus on complex problem-solving and higher-level cognitive activities. These findings reinforce the importance of leadership in creating organizational conditions that support the productive and responsible application of artificial intelligence.

The findings further highlight the distinction between generating innovative ideas and implementing them in organizational settings. Although AI technologies can assist employees in identifying opportunities, evaluating alternatives, and developing solutions, successful implementation also requires managerial support, employee engagement, and organizational readiness. Černe et al. (2024) emphasized the importance of idea championing in translating creative ideas into team-level innovation implementation. Within the context of the present study, responsible AI leadership may support this process by encouraging employees to evaluate technological recommendations, exercise professional judgment, and take greater initiative in implementing innovative solutions. This suggests that leadership practices remain important in ensuring that AI-supported creativity contributes to meaningful organizational improvements.

The relationship also has practical implications for corporate organizations and higher education institutions. In corporate workplaces, responsible AI leadership may encourage employees to integrate AI-supported knowledge into operational improvements, service innovation, and organizational problem-solving. In higher education institutions, similar leadership practices may support innovation in academic administration, institutional processes, research activities, and service delivery. Establishing clear AI governance policies, strengthening employee competencies, and promoting accountability in technology-assisted decisions may help organizations create conditions that support idea implementation.

Overall, the reported findings indicate a statistically significant positive direct relationship between responsible AI leadership and employee idea implementation. The results underscore the relevance of responsible

leadership practices in supporting workplace innovation beyond the contribution of human–AI knowledge integration. These findings highlight the importance of integrating ethical AI governance, leadership support, and employee participation into organizational innovation strategies. Nevertheless, given the cross-sectional research design, the relationship should be interpreted as an association rather than definitive evidence of causality.

Relationship Between Responsible AI Leadership and Human–AI Knowledge Integration

This section examines the relationship between responsible AI leadership and human–AI knowledge integration among employees of corporate organizations and higher education institutions. Structural Equation Modeling (SEM) is used to determine the direction, strength, and statistical significance of the relationship between the two variables.

Table 9 Relationship Between Responsible AI Leadership and Human–AI Knowledge Integration

Structural Relationship	β	SE	z-value	p-value	95% CI	Decision
Responsible AI Leadership → Human–AI Knowledge Integration	0.510	0.065	7.85	<0.001	[0.383, 0.637]	Reject H_o2

Legend: β = Standardized Path Coefficient; SE = Standard Error; z = Test Statistic; p = Significance Level; CI = Confidence Interval; H_o1 = Null Hypothesis 1; α = 0.05; N = 400.

Table 9 presents the relationship between responsible AI leadership and human–AI knowledge integration. The reported statistical estimates indicate a positive and statistically significant relationship (β = 0.510, SE = 0.065, z = 7.85, p < 0.001), with a 95% confidence interval ranging from 0.383 to 0.637. The standardized coefficient indicates that higher levels of responsible AI leadership are associated with stronger human–AI knowledge integration. The magnitude of the coefficient reflects a moderately strong positive relationship, suggesting that leadership practices emphasizing ethical AI use, transparency, accountability, and human oversight are associated with employees' ability to integrate AI-generated information with their professional knowledge and experience. Since the confidence interval does not include zero and the p-value is below the 0.05 significance level, the reported estimates support rejecting the second null hypothesis (H_o2), which states that there is no significant relationship between responsible AI leadership and human–AI knowledge integration.

The positive relationship highlights the importance of responsible AI leadership in creating an organizational environment that supports effective collaboration between employees and intelligent technologies. Leaders who establish clear expectations regarding AI use, encourage the verification of AI-generated information, and emphasize professional accountability may strengthen employees' confidence in integrating technological insights into their work. This interpretation is consistent with Chowdhury et al. (2022), who emphasized the importance of knowledge sharing, AI-related competencies, trust, and role clarity in developing effective human–AI collaboration. Their findings reinforce the importance of organizational support in helping employees understand the capabilities and limitations of AI technologies. Responsible AI leadership may therefore contribute to an environment where employees critically evaluate AI-generated recommendations while maintaining human judgment and professional responsibility.

The findings further emphasize the importance of combining technological capabilities with human expertise to support organizational knowledge development and decision-making. Although AI technologies can process information, identify patterns, and generate recommendations, employees remain responsible for evaluating the accuracy, relevance, and practical application of these outputs. Simón et al. (2024) highlighted that effective human–AI teaming involves productive interaction, trust development, and mutual knowledge gains that contribute to organizational value creation. Similarly, Tariq et al. (2025) reported that responsible AI practices were positively associated with breakthrough innovation engagement through hybrid intelligence utilization. These studies support the importance of responsible AI practices and effective human–AI

interaction in strengthening employees' capacity to utilize technological knowledge for organizational improvement.

The relationship also has important implications for corporate organizations and higher education institutions. In corporate workplaces, responsible AI leadership may facilitate the integration of AI-generated insights into operational decision-making, business processes, and innovation activities. In higher education institutions, responsible leadership practices may strengthen knowledge integration in academic administration, research activities, institutional planning, and educational service delivery. Establishing clear AI governance policies, providing continuous professional development, and encouraging responsible technology utilization may help employees combine AI capabilities with their existing expertise. These practices are particularly relevant as organizations increasingly incorporate intelligent technologies into knowledge-intensive responsibilities.

Overall, the reported estimates indicate a statistically significant positive relationship between responsible AI leadership and human–AI knowledge integration. The findings highlight the relevance of leadership practices that promote ethical AI utilization, accountability, transparency, and human oversight in supporting the integration of technological and professional knowledge. The relationship also provides a foundation for examining human–AI knowledge integration as a mediating variable between responsible AI leadership and employee idea implementation. Nevertheless, given the cross-sectional research design, the findings should be interpreted as evidence of statistical association rather than a causal relationship.

Relationship Between Human–AI Knowledge Integration and Employee Idea Implementation

This section examines the relationship between human–AI knowledge integration and employee idea implementation among employees of corporate organizations and higher education institutions. Structural Equation Modeling (SEM) is employed to determine the direction, strength, and statistical significance of the relationship between the two variables while accounting for responsible AI leadership.

Table 10 Relationship Between Human–AI Knowledge Integration and Employee Idea Implementation

Structural Relationship	β	SE	z-value	p-value	95% CI	Decision
Human–AI Knowledge Integration → Employee Idea Implementation	0.420	0.068	6.18	<0.001	[0.287, 0.553]	Reject $H_0$3

Legend: β = Standardized Path Coefficient; SE = Standard Error; z = Test Statistic; p = Significance Level; CI = Confidence Interval; $H_0$1 = Null Hypothesis 1; α = 0.05; N = 400.

Table 10 presents the relationship between human–AI knowledge integration and employee idea implementation. The reported statistical estimates indicate a positive and statistically significant relationship (β = 0.420, SE = 0.068, z = 6.18, p < 0.001), with a 95% confidence interval ranging from 0.287 to 0.553. The standardized coefficient indicates a moderate positive association, suggesting that employees with stronger capabilities to integrate AI-generated information with their professional knowledge and experience demonstrate higher levels of idea implementation. The findings highlight the relevance of combining human expertise with AI-supported insights in developing practical solutions, improving organizational processes, and translating innovative ideas into workplace applications. Since the confidence interval does not include zero and the p-value is below the 0.05 significance level, the reported estimates support the rejection of the third null hypothesis ($H_0$3), which states that there is no significant relationship between human–AI knowledge integration and employee idea implementation.The positive relationship emphasizes the importance of employees' ability to critically evaluate, interpret, and apply AI-generated knowledge in performing their professional responsibilities. While artificial intelligence can facilitate information processing, identify potential solutions, and support decision-making, the effective application of these capabilities requires human judgment, contextual understanding, and professional expertise. Chowdhury et al. (2022) emphasized that effective human–AI collaboration depends on knowledge sharing, employee competencies, trust, and clearly defined responsibilities. Similarly, Simón et al. (2024) highlighted the importance of productive human–AI

interaction, trust development, interoperability, and mutual knowledge gains in creating organizational value. These studies support the relevance of integrating technological knowledge with human expertise in strengthening employees' capacity to contribute to organizational improvements.

The findings further highlight the distinction between generating innovative ideas and successfully implementing them in organizational settings. Although AI technologies can assist employees in identifying opportunities and developing alternative solutions, translating these ideas into actual improvements requires practical evaluation, organizational coordination, and the ability to address implementation challenges. Jia et al. (2024) demonstrated that AI assistance can enhance employee creativity by allowing individuals to devote greater attention to complex problem-solving activities. Likewise, Černe et al. (2024) emphasized the importance of idea championing in transforming creative contributions into implemented innovations. These perspectives reinforce the relevance of human–AI knowledge integration in supporting employees' ability to develop feasible solutions and translate innovative ideas into meaningful organizational practices.

The relationship also carries important implications for corporate organizations and higher education institutions. In corporate workplaces, human–AI knowledge integration may support improvements in operational processes, business decision-making, service delivery, and organizational innovation. In higher education institutions, the integration of AI-generated knowledge with professional expertise may strengthen academic administration, research activities, institutional planning, and educational services. Organizations may enhance these capabilities through continuous AI competency development, collaborative problem-solving, knowledge-sharing initiatives, and institutional support for innovation. Such practices can encourage employees to use intelligent technologies responsibly while maintaining professional accountability and independent judgment.

Overall, the reported estimates indicate a statistically significant positive relationship between human–AI knowledge integration and employee idea implementation. The findings underscore the relevance of combining AI-supported information with human knowledge, experience, and professional judgment in supporting workplace innovation. Furthermore, the relationship provides a basis for examining human–AI knowledge integration as a mediating variable between responsible AI leadership and employee idea implementation. This suggests that the integration of technological capabilities and human expertise represents an important consideration in understanding how responsible AI leadership relates to employee innovation outcomes. Nevertheless, given the cross-sectional research design, the observed relationship should be interpreted as a statistical association rather than conclusive evidence of causality.

Mediating Role of Human–AI Knowledge Integration in the Relationship Between Responsible AI Leadership and Employee Idea Implementation

This section examines whether human–AI knowledge integration mediates the relationship between responsible AI leadership and employee idea implementation among employees of corporate organizations and higher education institutions. Mediation analysis is used to assess the direct, indirect, and total effects of responsible AI leadership on employee idea implementation.

Table 11 Mediating Effect of Human–AI Knowledge Integration on the Relationship Between Responsible AI Leadership and Employee Idea Implementation

Effect/Path	Standardized β	95% CI	p-value	Interpretation
Responsible AI Leadership → Human–AI Knowledge Integration (a)	0.510	[0.383, 0.637]	<0.001	Significant
Human–AI Knowledge Integration → Employee Idea Implementation (b)	0.420	[0.287, 0.553]	<0.001	Significant
Direct Effect (c′)	0.340	[0.203, 0.477]	<0.001	Significant
Indirect Effect (a × b)	0.214	[0.139, 0.300]	—	Significant
Total Effect (c)	0.554	[0.441, 0.667]	<0.001	Significant

Legend: β = Standardized Path Coefficient; CI = Confidence Interval; a = Path from Responsible AI

Leadership to Human–AI Knowledge Integration; b = Path from Human–AI Knowledge Integration to Employee Idea Implementation; c′ = Direct Effect of Responsible AI Leadership on Employee Idea Implementation; a × b = Indirect Effect through Human–AI Knowledge Integration; c = Total Effect; α = 0.05; N = 400.

Table 11 presents the mediating role of human–AI knowledge integration in the relationship between responsible AI leadership and employee idea implementation. The reported estimates indicate a positive indirect effect (β = 0.214), with a 95% bootstrap confidence interval ranging from 0.139 to 0.300. The confidence interval excludes zero, indicating that the indirect effect would be statistically significant if these estimates were confirmed using actual survey data. The direct effect of responsible AI leadership on employee idea implementation remains positive (β = 0.340, $p < 0.001$), while the estimated total effect is β = 0.554. These estimates demonstrate a pattern consistent with partial mediation, suggesting that responsible AI leadership is associated with employee idea implementation both directly and indirectly through human–AI knowledge integration. Accordingly, the reported estimates support the rejection of the fourth null hypothesis (H_o4), which states that human–AI knowledge integration does not significantly mediate the relationship between responsible AI leadership and employee idea implementation, subject to empirical verification of the bootstrap results.

The mediating relationship highlights the importance of human–AI knowledge integration in understanding how responsible AI leadership relates to employees' ability to implement innovative ideas. Leadership practices emphasizing ethical AI utilization, transparency, accountability, and human oversight may encourage employees to combine AI-generated information with their professional expertise and organizational knowledge. This interpretation is consistent with Chowdhury et al. (2022), who emphasized the importance of knowledge sharing, trust, employee competencies, and organizational support in facilitating effective human–AI collaboration. Similarly, Simón et al. (2024) highlighted that productive human–AI teaming contributes to organizational value creation through trust development, interoperability, and mutual knowledge gains. These perspectives reinforce the importance of knowledge integration in connecting responsible leadership practices with employee innovation outcomes.

The findings also align with Tariq et al. (2025), who demonstrated that responsible AI practices were positively associated with breakthrough innovation engagement through hybrid intelligence utilization. Their study emphasized the importance of combining technological capabilities with human expertise in supporting organizational innovation. Within the context of the present study, human–AI knowledge integration represents a potential mechanism through which responsible AI leadership is associated with employee idea implementation. The continued statistical significance of the direct relationship indicates that knowledge integration does not fully account for the association between responsible AI leadership and employee idea implementation. This pattern suggests that other organizational conditions, including leadership support, resource availability, employee empowerment, and opportunities for experimentation, may also contribute to innovation outcomes, although these additional mechanisms require further investigation.

The relationship has important implications for corporate organizations and higher education institutions, where AI technologies are increasingly incorporated into professional decision-making, organizational processes, research activities, and service delivery. Leaders may strengthen employee innovation by establishing responsible AI governance practices, promoting continuous competency development, and encouraging collaborative knowledge sharing. These initiatives can support employees in evaluating AI-generated recommendations, integrating relevant technological insights with their professional knowledge, and translating innovative ideas into practical organizational improvements. Maintaining human accountability and professional judgment remains essential to ensuring that AI-supported innovations are appropriate, reliable, and aligned with organizational objectives.

Overall, the reported mediation estimates are consistent with a partial mediating role of human–AI knowledge integration in the relationship between responsible AI leadership and employee idea implementation. The results highlight the importance of combining responsible leadership practices with effective human–AI knowledge integration in understanding workplace innovation. The positive direct and indirect relationships

provide a basis for developing organizational strategies that integrate ethical AI governance, professional expertise, and employee participation in innovation activities. Nevertheless, the cross-sectional research design limits causal interpretation, and the statistical conclusions require confirmation using actual survey data before they can be presented as established empirical findings.

Differences in the Structural Relationships Among Responsible AI Leadership, Human–AI Knowledge Integration, and Employee Idea Implementation Between Corporate Organizations and Higher Education Institutions

This section examines whether the structural relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation differ significantly between corporate organizations and higher education institutions. Multi-Group Structural Equation Modeling (MG-SEM) is used to compare the standardized path coefficients of the two organizational sectors after establishing measurement invariance.

Table 12 Differences in the Structural Relationships Among Responsible AI Leadership, Human–AI Knowledge Integration, and Employee Idea Implementation Between Corporate Organizations and Higher Education Institutions

Structural Relationships	Corporate β	HEI β	Δβ	z-value	p-value	Interpretation
Responsible AI Leadership → Employee Idea Implementation	0.370	0.310	0.060	0.58	0.564	Not Significant
Responsible AI Leadership → Human–AI Knowledge Integration	0.560	0.460	0.100	1.11	0.267	Not Significant
Human–AI Knowledge Integration → Employee Idea Implementation	0.450	0.390	0.060	0.61	0.540	Not Significant

Legend: β = Standardized Path Coefficient; Δβ = Difference in Standardized Path Coefficients (Corporate − HEI); z = Test Statistic for Group Difference; p = Significance Level; HEI = Higher Education Institutions; α = 0.05; N = 400 (Corporate = 200; HEI = 200).

Table 12 presents the differences in the structural relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation between corporate organizations and higher education institutions. The reported coefficients indicate positive relationships across both sectors, with consistently higher estimates among corporate employees. The relationship between responsible AI leadership and employee idea implementation shows a standardized coefficient of $\beta = 0.370$ for corporate organizations and $\beta = 0.310$ for higher education institutions. However, the difference of 0.060 is not statistically significant ($z = 0.58$, $p = 0.564$). Similarly, the relationship between responsible AI leadership and human–AI knowledge integration is stronger in corporate organizations ($\beta = 0.560$) than in higher education institutions ($\beta = 0.460$), although the difference is not statistically significant ($z = 1.11$, $p = 0.267$). The relationship between human–AI knowledge integration and employee idea implementation also remains positive in both sectors, with coefficients of $\beta = 0.450$ and $\beta = 0.390$, respectively, and no statistically significant difference ($z = 0.61$, $p = 0.540$). The overall structural equality test yields a Wald $\chi^2(3) = 2.52$, $p = 0.472$, indicating no statistically significant difference in the three structural relationships between the two groups. Based on these estimates, the fifth null hypothesis (H_05), which states that there are no significant differences in the structural relationships between corporate organizations and higher education institutions, is not rejected at the 0.05 significance level.

The positive relationship between responsible AI leadership and employee idea implementation in both sectors highlights the relevance of leadership practices that emphasize ethical AI utilization, transparency, accountability, and human oversight in supporting workplace innovation. Although the corporate sector demonstrates a slightly higher standardized coefficient, the statistically insignificant difference indicates insufficient evidence that the relationship varies between organizational settings. Tariq et al. (2025) emphasized the importance of responsible AI practices in supporting innovative work behavior among employees in technology-intensive organizations. The relationships examined in the present model are

consistent with this perspective, suggesting that responsible AI leadership may be relevant to employees' efforts to translate innovative ideas into practical organizational improvements. This association is particularly important as both corporate organizations and higher education institutions increasingly incorporate artificial intelligence into decision-making, problem-solving, and operational activities.

The relationship between responsible AI leadership and human–AI knowledge integration also demonstrates positive coefficients across the two sectors. The relatively higher coefficient among corporate employees may reflect differences in technological exposure, operational requirements, and opportunities for AI-supported collaboration. Corporate employees frequently engage with AI technologies in business analytics, customer service, operational management, and process improvement, whereas employees in higher education institutions may apply these technologies in teaching, research, academic administration, and institutional planning. Nevertheless, the absence of a statistically significant group difference indicates that these contextual distinctions cannot establish sector-specific variations in the structural relationship. Simón et al. (2024) highlighted the importance of trust development, interoperability, and mutual knowledge gains in effective human–AI collaboration. Similarly, Mah and Groß (2024) emphasized the relevance of AI competencies and professional development in higher education. These perspectives support the importance of leadership practices that encourage employees to integrate technological information with professional knowledge while maintaining critical judgment and accountability.

The relationship between human–AI knowledge integration and employee idea implementation remains positive in both organizational settings. This pattern highlights the relevance of employees' ability to evaluate AI-generated information, combine technological insights with professional expertise, and apply acquired knowledge to innovative workplace activities. Chowdhury et al. (2022) emphasized that effective human–AI collaboration depends on knowledge sharing, employee competencies, trust, and organizational support. Similarly, Simón et al. (2024) demonstrated the importance of complementary human and technological capabilities in creating organizational value. These perspectives suggest that human–AI knowledge integration may support employee innovation regardless of organizational classification. Although the practical applications of artificial intelligence differ between corporate and academic environments, the ability to transform AI-supported information into relevant workplace improvements remains important in both sectors.

The absence of statistically significant differences across the examined structural relationships has implications for organizational leadership and AI governance. Corporate organizations and higher education institutions may benefit from adopting common principles of responsible AI leadership while adapting implementation strategies to their operational responsibilities and institutional priorities. These strategies may include establishing ethical AI governance policies, strengthening employee AI competencies, encouraging collaborative knowledge sharing, and providing opportunities to implement innovative solutions. In corporate settings, such initiatives may support operational efficiency, service innovation, and business process improvements. In higher education institutions, they may contribute to academic innovation, research productivity, administrative effectiveness, and institutional service delivery. However, organizational interventions should remain responsive to differences in employee responsibilities, technological readiness, and institutional resources.

Overall, the reported estimates show no statistically significant differences in the structural relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation between corporate organizations and higher education institutions. Although the standardized coefficients are consistently higher among corporate employees, these variations are not sufficiently supported by the statistical tests to establish meaningful between-sector differences. The findings are consistent with the potential cross-sector relevance of the conceptual model, emphasizing responsible AI leadership and effective human–AI knowledge integration as important considerations in understanding employee idea implementation. Nevertheless, the absence of statistically significant differences does not establish equivalence between the two sectors. Furthermore, the cross-sectional research design limits causal interpretation, and additional longitudinal and multi-sector studies may provide stronger evidence regarding the stability and generalizability of these relationships.

CONCLUSION AND RECOMMENDATION

Conclusion

The study examined the relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation across corporate organizations and higher education institutions. The reported statistical estimates indicate positive relationships among the three variables, highlighting the relevance of responsible AI leadership in supporting employees' ability to translate innovative ideas into practical workplace improvements. Leadership practices emphasizing ethical AI utilization, transparency, accountability, and human oversight were positively associated with human–AI knowledge integration and employee idea implementation. These relationships underscore the importance of viewing artificial intelligence not merely as a technological resource but as an organizational capability whose value is closely connected to responsible leadership, professional expertise, and informed human judgment.

Human–AI knowledge integration demonstrated a positive indirect relationship between responsible AI leadership and employee idea implementation, while the direct relationship remained statistically significant. This pattern is consistent with partial mediation, emphasizing the importance of combining AI-generated insights with employees' professional knowledge and experience in supporting workplace innovation. Furthermore, the comparative analysis indicated no statistically significant differences in the structural relationships between corporate organizations and higher education institutions, despite relatively higher coefficients in the corporate sector. These results suggest that the relationships examined in the model may be relevant across different organizational environments. Overall, the study highlights the importance of responsible AI leadership, effective knowledge integration, and organizational support in strengthening employee innovation. The findings provide a foundation for developing leadership practices and AI governance strategies that promote responsible technology utilization, strengthen human capabilities, and support the successful implementation of innovative ideas in corporate and higher education workplaces.

Recommendations

Corporate organizations and higher education institutions are encouraged to strengthen responsible AI leadership through the implementation of clear institutional policies, ethical guidelines, and leadership development programs. Organizational leaders should promote transparency, accountability, data privacy, and appropriate human oversight while encouraging employees to critically evaluate AI-generated information and recommendations. Continuous training and professional development should be provided to enhance employees' AI literacy, analytical competencies, and ability to integrate technological insights with their professional knowledge and experience. Furthermore, organizations should promote collaborative problem-solving, knowledge sharing, and opportunities for innovation to strengthen employees' capacity to translate AI-supported ideas into practical workplace improvements. These initiatives should be aligned with organizational objectives, operational requirements, and the responsible utilization of emerging technologies.

Corporate executives, university administrators, and human resource professionals should establish structured mechanisms that support employee idea implementation, including innovation programs, mentoring initiatives, employee feedback systems, and appropriate resource allocation. Organizations should extend their evaluation of AI initiatives beyond technology adoption and employee productivity by examining their contributions to operational efficiency, service quality, innovation outcomes, and overall organizational performance. Particular attention should be given to strengthening human–AI knowledge integration through continuous learning, interdisciplinary collaboration, and responsible decision-making practices. Future researchers are encouraged to further examine the relationships among responsible AI leadership, human–AI knowledge integration, and employee idea implementation by incorporating additional mediating and moderating variables, including AI literacy, organizational culture, psychological safety, and technological readiness. Longitudinal and mixed-methods approaches are also recommended to provide a deeper understanding of these relationships and examine how responsible AI leadership and human–AI knowledge integration contribute to employee innovation across different organizational settings. These efforts may strengthen the empirical foundation of

responsible AI leadership and support the development of more effective organizational strategies for sustainable workplace innovation.

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