ORIGINAL ARTICLE

Decision tree analysis of researchers' beliefs in AI: effects of awareness and institutional support

Roaa S. Bogdadi[1*], Nahid A. Qushmaq[1], Marivel M. De Guzman[2] Rahaf Al Hasheem[3], Wijdan A. Baeshen[4], Sarah M. Aljuaid[4]

ABSTRACT

Background: The increasing integration of artificial intelligence (AI) in scientific research has raised important questions about how researchers' beliefs are shaped by cognitive and institutional factors. While previous studies have focused on technological capabilities and ethical concerns, limited attention has been given to how everyday awareness of AI and perceived organizational support influence acceptance of AI's contribution in research.

Methods: A cross-sectional survey was conducted among 1,379 researchers to assess their beliefs regarding AI's contribution to scientific research, awareness of AI in daily and research contexts, and perceived institutional support. A decision tree classification model was developed to predict belief categories ("Yes," "Probably," or "No") based on these variables.

Results: The model achieved an overall accuracy of 80.07%, with the highest predictive performance in the "Yes" category. Daily AI awareness emerged as the most influential predictor, followed by perceived organizational support and awareness of AI in research context settings. The decision tree structure provided clear and interpretable insights into how these variables interact to shape researchers' beliefs.

Conclusion: Researchers' acceptance of AI in scientific research is primarily driven by personal familiarity with AI and the level of institutional support. These findings emphasize the importance of enhancing both practical exposure to AI and supportive organizational environments to promote responsible and effective AI adoption in research.

Keywords: Artificial intelligence, data science applications in education, research perception, institutional support, interdisciplinary projects.

Introduction

Artificial intelligence (AI) has fundamentally transformed scientific research by reshaping knowledge production, processing, and dissemination across disciplines. From literature review and data analysis to research design, hypothesis generation, and communication, AI technologies are increasingly being integrated into research activities [1,2]. While these advancements improve productivity, they also raise important questions regarding the factors influencing researchers' willingness to adopt AI tools. Understanding these factors is essential for institutions aiming to integrate AI responsibly into research systems.

Technology adoption has traditionally been explained using models such as the technology acceptance model (TAM) and theory of planned behavior, which emphasize perceived usefulness, ease of use, and behavioral intention [3,4]. However, these models often overlook institutional and contextual influences. To address this limitation, the present study applies an extended TAM within a socio-technical systems perspective, recognizing that beliefs

Correspondence to: Roaa S. Bogdadi
*Research Department, King Abdullah Medical Complex in Jeddah, Jeddah, Saudi Arabia.
Email: funoon.ibda.2025@gmail.com
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about AI are shaped not only by perceived usefulness but also by awareness and institutional support. Thus, awareness, perceived institutional support, and belief in AI are treated as interconnected determinants of AI acceptance in research contexts.

Awareness is a key factor influencing belief in AI's contribution to research. Individuals familiar with AI applications in daily life-such as digital assistants, search algorithms, and automated recommendation systems-are more likely to adopt AI in professional settings [5]. Similarly, researchers exposed to AI tools within their disciplines, including AI-assisted literature review agents, data analytics applications, and automated peer-review systems, are more likely to recognize their value. Previous studies have shown that awareness of AI in both daily and research contexts contributes to trust, reduces anxiety, and strengthens willingness to engage with AI technologies [5,6,7].

Institutional support is equally important in shaping researchers' perceptions of AI. Organizational elements such as training programs, leadership support, technical infrastructure, and ethical guidelines can strengthen or weaken confidence in AI tools [8]. Institutions that invest in AI integration and establish governance frameworks tend to promote acceptance, whereas limited institutional support may contribute to resistance, particularly in relation to concerns about autonomy, data privacy, academic integrity, and responsible AI use [9–11]. Previous studies have also shown that institutional support can improve learning outcomes and mitigate anxiety associated with AI adoption [11,7].

Beyond technological functionality, psychological and emotional factors also influence researchers' readiness to adopt AI. AI adoption is a cognitively and emotionally complex process involving both curiosity and apprehension [12]. Trust, anxiety, and individual perceptions toward automation have been identified as important influences on AI engagement, particularly in academic and research settings [6,12]. Greater exposure to AI tools tends to reduce hesitation and increase trust, whereas limited exposure may reinforce uncertainty and resistance [5,7].

Ethical concerns further shape researchers' perceptions of AI integration in scientific research. Issues related to algorithmic opacity, authorship, data ownership, academic integrity, and responsible AI governance remain central to discussions surrounding AI adoption [10,11]. Previous studies have argued that general ethical principles alone may not adequately address context-specific risks associated with AI deployment, emphasizing the importance of transparency, governance, and explainability in institutional decision-making [13,14].

Despite increasing research on AI perceptions, several limitations remain. Many previous studies rely primarily on descriptive statistics and lack interpretable predictive approaches capable of identifying actionable determinants of AI acceptance [15]. Although machine learning techniques offer strong analytical capabilities, their usefulness for institutional decision-making may be reduced when prediction processes are not transparent. This limitation has led to growing interest in explainable artificial intelligence (XAI), which emphasizes transparency and interpretability in predictive modeling [16]. Concerns regarding opaque machine learning systems further highlight the need for explainable models capable of clarifying how cognitive and institutional factors interact to shape researchers' beliefs regarding AI adoption [17].

To address these limitations, this study employs a decision tree classification model to predict researchers' beliefs in AI's contribution to scientific research using three variables: awareness of AI in daily life, awareness of AI in research contexts, and perceived institutional support. Decision tree models provide transparent and hierarchical structures that clearly illustrate how combinations of factors influence belief categories, offering both predictive and analytical value for institutional decision-making.

In sum, this research bridges theoretical and practical gaps by integrating cognitive, institutional, ethical, and technical perspectives. It provides a transparent framework for understanding how researchers form beliefs about AI in scientific research and how these beliefs can guide institutional strategies for responsible AI integration in the evolving landscape of digital transformation.

This study aimed to identify the key predictors influencing researchers' beliefs that AI contributes positively to scientific research using an interpretable decision tree classification model. Specifically, the study examined the influence of awareness of AI in scientific research, awareness of AI in daily life, and perceived institutional support on researchers' beliefs regarding AI's contribution to research. In addition, the study utilized a decision tree model to classify belief levels based on combinations of awareness and institutional support factors, thereby providing an interpretable framework for understanding AI acceptance in research environments.

Methods

This study employed a quantitative, cross-sectional research design using survey data to investigate how researchers' awareness and perceived institutional support for AI influence their belief in AI's contribution to scientific research, consistent with standard cross-sectional study methodology described by Setia [18]. A decision tree classification model was utilized to identify the key predictors that distinguish between varying levels of belief about AI's role in research, based on established classification tree methodologies described by Breiman et al. [15,19]. This model was selected for its ability to extract interpretable patterns and rule-based classifications from categorical survey data.

Participants and sampling

A total of 1,379 researchers from academic institutions across multiple regions participated in this study. Participants were recruited using a non-probability convenience sampling approach. Eligible participants were required to be actively engaged in academic or applied scientific research within the disciplines of health sciences, engineering, computer science, education, or social sciences.

To be included in the study, participants had to demonstrate basic familiarity with AI tools either in daily life, such as digital assistants and algorithms, or in research contexts, including AI-based analysis platforms. Participants were also required to be affiliated with a university, research center, or academic institution, be at least 18 years of age, and provide informed consent prior to participation.

Individuals were excluded if they had no prior exposure to AI in either personal or research settings, were not actively involved in research activities, or submitted incomplete questionnaires with less than 90% completion. Participants who declined to provide informed consent were also excluded from the study.

These criteria ensured that respondents had sufficient contextual exposure to reflect meaningfully on their beliefs about AI in scientific research. We collected demographic information about the respondents' academic discipline, rank, and experience with AI for descriptive purposes. Although the sampling method limits the generalizability of the findings, the size and diversity of the sample provided meaningful insights into how awareness of and support from institutions shape beliefs about AI's role in helping researchers.

The non-probability convenience sampling method presented some limitations, particularly the potential for self-selection bias based on the voluntary participation of respondents and depending on participants' familiarity with or interest in AI. Therefore, it is conceivable that the findings may not generalize to all researchers, particularly those in underrepresented disciplines or in institutions with little-known infrastructure regarding AI.

Instrumentation

Data were collected using a self-administered online questionnaire designed to assess researchers' beliefs and perceptions related to AI in scientific research. The instrument consisted of three major components addressing belief constructs, awareness indicators, and perceived institutional support.

The belief construct section included items measuring participants' perceptions regarding whether AI contributes positively to scientific research. Responses were categorized into three levels ("Yes," "Probably," and "No") based on participants' Likert-scale scores, consistent with established approaches for simplifying Likert-scale data in analytical modeling [20]. The awareness section assessed participants' familiarity with AI in both every day and research-related contexts. This included awareness of AI applications in daily life, such as digital assistants, recommender systems, and smart devices, as well as awareness of AI in research contexts, including AI-assisted data analysis, writing tools, and research software.

The institutional support section evaluated participants' perceptions of organizational support for AI integration. Items addressed the availability of AI-related training, technical infrastructure, leadership encouragement, and ethical guidance related to AI implementation within research environments.

All questionnaire items were measured using a 5-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). For analytical purposes, belief scores were collapsed into three categories to serve as the outcome variable in the decision tree model. Responses of 1 or 2 were coded as "No," a response of 3 was coded as "Probably," and responses of 4 or 5 were coded as "Yes." This categorization approach aligns with common practices in simplifying Likert-scale data for classification modeling while maintaining interpretive clarity.

The overall survey instrument demonstrated strong internal consistency, with a Cronbach's alpha of 0.91, consistent with accepted standards for internal reliability assessment described by Cronbach [21]. Reliability was also acceptable across all subscales, including Belief in AI's Contribution to Research (4 items, $\alpha = 0.88$), Awareness of AI (6 items across daily and research contexts, $\alpha = 0.87$), and Perceived Institutional Support (5 items, $\alpha = 0.89$). These findings indicate high reliability across all measured constructs.

Data analysis

Descriptive statistics were used to summarize participant demographic data and important patterns in responses. For the main analysis, a decision tree classifier was used from the scikit-learn library in the Python programming language. The target variable was whether or not participants believed that AI would contribute to scientific research, classified into three classes: "Yes," "Probably," and "No." This belief variable was constructed using respondents' Likert-scale responses and was operationalized as a categorical variable with three levels, as described in the Instrumentation section.

The predictor variables included awareness of AI in everyday life, awareness of AI in research contexts, and perceived institutional support for AI integration. The decision tree model was developed using the Gini impurity criterion with a maximum depth of four to maintain interpretability. Model performance was evaluated using classification accuracy, confusion matrix metrics across classes, and the area under the receiver operating characteristic curve (AUC-ROC) using a one-versus-rest approach, consistent with established methods for evaluating diagnostic and classification performance [22].

Because the outcome variable was imbalanced, particularly due to the limited representation of the "No" category, several class-balancing approaches were considered. Although synthetic oversampling techniques such as SMOTE were evaluated, they were not applied in the final model in order to preserve the natural distribution of responses. Instead, a stratified train-test split was used to maintain proportional class representation within the training (80%) and testing (20%) datasets, thereby supporting more reliable model evaluation while preserving class integrity.

The stratified train-test split provided an initial form of validation, but no *k*-fold cross-validation was performed. *K*-fold cross-validation was not performed to preserve the interpretability and transparency of the decision rules. However, cross-validation is an accepted multi-sample validation approach that could improve robustness and generalizability. Future studies may incorporate this technique to confirm the stability of predictive rules across samples.

This analytic approach was selected for its transparency, simplicity, and alignment with the study's goal of generating interpretable, rule-based insights into belief formation related to AI adoption in research environments.

Ethical approval

Ethical clearance was granted by an institutional review board in accordance with international and national research ethics standards. All procedures adhered to the Declaration of Helsinki. Participation was voluntary and anonymous, and informed consent was obtained from all participants prior to data collection. Approval details are available upon request.

Results

This section presents the results of the multiclass decision tree model used to classify researchers' perceptions of AI in scientific research. The model utilized three key features, including awareness of AI in research contexts, awareness of AI in daily devices, and perceived institutional support. The target variable in the model consisted of three possible responses, "Yes," "No," and "Probably," all of which represented the belief that AI would improve scientific research. Tables and figures are presented to illustrate the model structure, classification rules, and predictive performance (Table 1 and Figure 1).

Descriptive summary of the dataset

A total of 1,379 survey responses were analyzed using a decision tree classifier to categorize perceptions regarding whether AI improves scientific research. The dataset included three response categories: "Yes," "Probably," and "No." Stratified sampling was applied by dividing the dataset into 80% training (n = 1,103) and 20% testing (n = 276) subsets while maintaining proportional class representation.

Among the 276 test samples, the class distribution was as follows: Yes = 215, Probably = 49, and No = 12. This imbalance influenced classification performance, particularly for the underrepresented "No" category. The decision tree classifier utilized three predictor variables: awareness of AI in research contexts, awareness of AI in daily devices, and perceived institutional support.

The decision tree structure followed the following order of importance: (1) awareness of AI in daily devices, (2) perceived institutional support, and (3) awareness of AI in research contexts (Figure 1). The model reached a maximum depth of four levels and generated five final classification rules (Table 2), along with descriptive classification metrics for each response category (Table 1).

Decision tree classification performance

The decision tree model achieved a total classification accuracy of 80.07% on the test set (n = 276). It performed strongly in predicting the "Yes" response (Precision = 0.81, Recall = 0.99), moderately for "Probably" (Precision = 0.64, Recall = 0.18), and poorly for "No" (all metrics = 0.00), likely due to class imbalance.

The confusion matrix comparing predicted class outcomes with actual class outcomes is presented in Table 1. The model achieved the highest accuracy in the "Yes" category, correctly classifying 212 of 215 cases. It classified the "Probably" category at moderate levels, while it showed poor classification performance for the "No" category, reflecting class imbalance owing to low representation in the dataset.

Key predictive decision rules

Table 2 summarizes five important decision rules from the tree model, which indicate the combinations of predictor thresholds that classify a respondent's belief in AI's contribution to research. Three of the rules had 100% confidence and provided interpretable logical flows that institutions can use in their assessments.

Feature importance and node structure

The feature hierarchy showed that participants with high awareness of AI use in everyday devices and strong perceived institutional support were more likely to perceive AI as improving scientific research. On the other hand, those with low awareness and low support showed stronger negative perceptions.

The feature importance ranking confirms the preeminence of awareness (whether in everyday use or research settings) and perceived institutional support (Figure 1).

Table 1. *Confusion matrix results.*

Actual →	Predicted: No	Predicted: Probably	Predicted: Yes	Total
No	0	2	10	12
Probably	1	9	39	49
Yes	0	3	212	215

This table presents the number of correctly and incorrectly classified cases across the three response categories ("Yes," "Probably," and "No"), revealing strengths and limitations of the decision tree classifier's predictive accuracy.

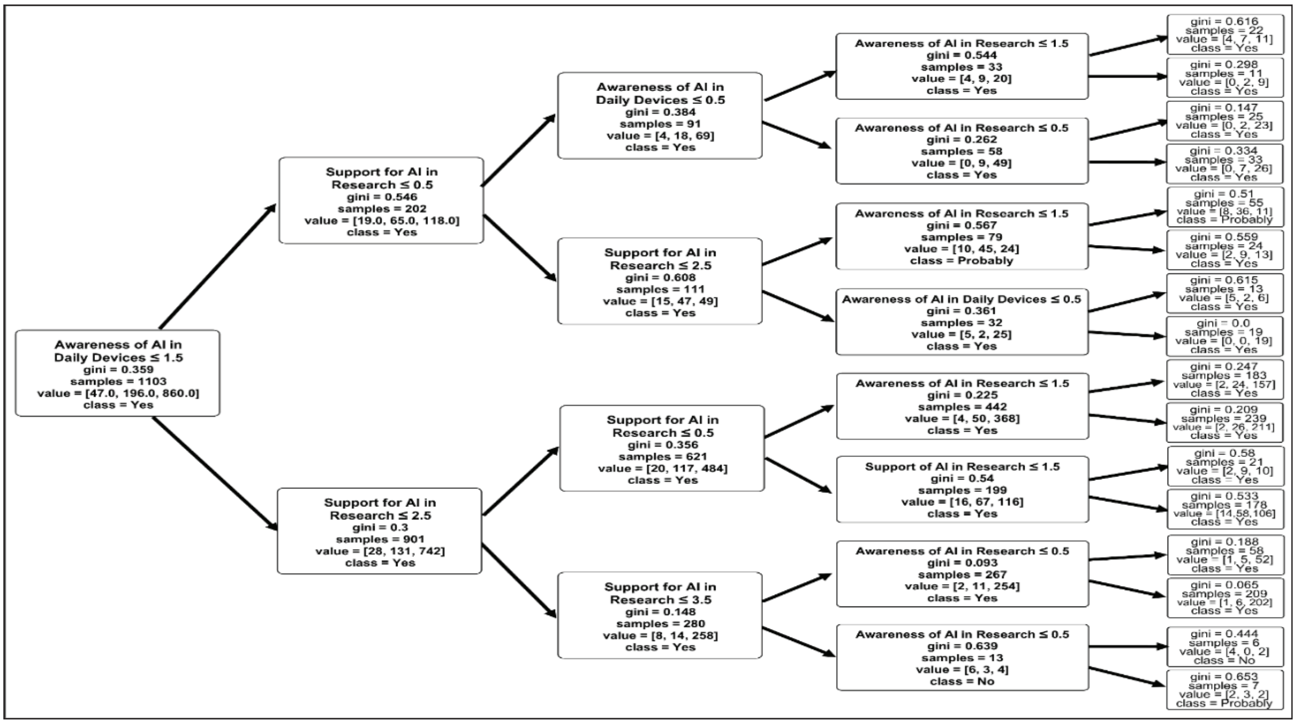

Figure 1. *Decision tree classification of AI perception based on awareness and support. This figure displays the hierarchical structure of the decision tree model used to classify researchers' beliefs in AI's contribution to scientific research. Splits are based on awareness of AI in daily life, institutional support, and awareness in research contexts. Each node shows the split criterion, sample size, class distribution, and predicted outcome. Lighter nodes indicate higher purity (lower Gini impurity), and the leaf nodes reflect final class predictions.*

Table 2. *Summary of key decision tree classification rules.*

	Decision path	Samples	Predicted class	Confidence
1	Devices ≤ -0.132 → Support ≤ 0.034	35	No	100.00%
2	Devices ≤ -0.132 → Support > 0.034	13	Yes	100.00%
3	Support ≤ -0.641	52	Yes	86.50%
4	Support > -0.641 → Awareness ≤ 1.404	11	Yes	54.50%
5	Support > -0.641 → Awareness > 1.404	41	Yes	95.10%

Note: The threshold values (e.g., "Devices ≤ -0.132") represent standardized predictor scores (z-scores), where values are normalized to a mean of 0 and a standard deviation of 1. These splits indicate the point at which the model divided the data based on relative levels of awareness or institutional support. Decision paths with 100% confidence applied to highly specific subsets of the sample and may not generalize broadly due to class imbalance.

ROC curve analysis

To further evaluate model performance, a multiclass ROC curve was plotted using a one-versus-rest strategy. The AUC scores were: *Yes: 0.7020, Probably: 0.6631, No: 0.7289.*

The AUC scores indicated modest discriminative ability for the "Yes" (0.70) and "No" (0.73) categories. The "Probably" class was more difficult to classify (AUC = 0.66), reflecting both semantic ambiguity and class overlap. These results suggest that while the model can moderately distinguish clear positive or negative beliefs, mid-level responses remain challenging to separate with high reliability (Table 3).

The AUC scores indicated moderate discriminative ability, particularly for the "Yes" and "No" classes, whereas the "Probably" class remained more difficult to predict accurately due to semantic ambiguity and class imbalance.

Figure 2 illustrates the ROC curves using a one-versus-rest approach for each class. These visual plots complement Table 3, confirming that the model performs best when classifying strong positive or negative beliefs but struggles with mid-level responses.

Discussion

This study investigated individual-level cognitive beliefs, domain-specific awareness, and institutional support, and their interaction in shaping researchers' views of AI integration in scientific research. The decision tree model provided a structured, rule-based approach to classify conditions that fulfilled the study's objectives.

Overall findings indicated that positive views of AI were not solely driven by perceptions that AI replaces human

__Table 3.__ AUC scores and interpretation by predicted class.

Class	AUC score	Interpretation
No	0.73	The model shows moderate ability to distinguish the "No" class from others. Despite the poor classification metrics in the confusion matrix, this AUC score suggests that the model can rank "No" instances somewhat effectively when probability thresholds are adjusted.
Probably	0.66	The model has relatively weak performance in predicting the "Probably" class. The lower AUC reflects challenges in separating "Probably" from the neighboring classes, likely due to semantic overlap and fewer representative samples in this category.
Yes	0.70	The model performs reasonably well in detecting the "Yes" class, which is the dominant class in the dataset. This score aligns with the high recall and precision reported in the classification metrics.

Class-specific AUC scores and corresponding interpretations summarizing the decision tree model's discriminative performance for each category.

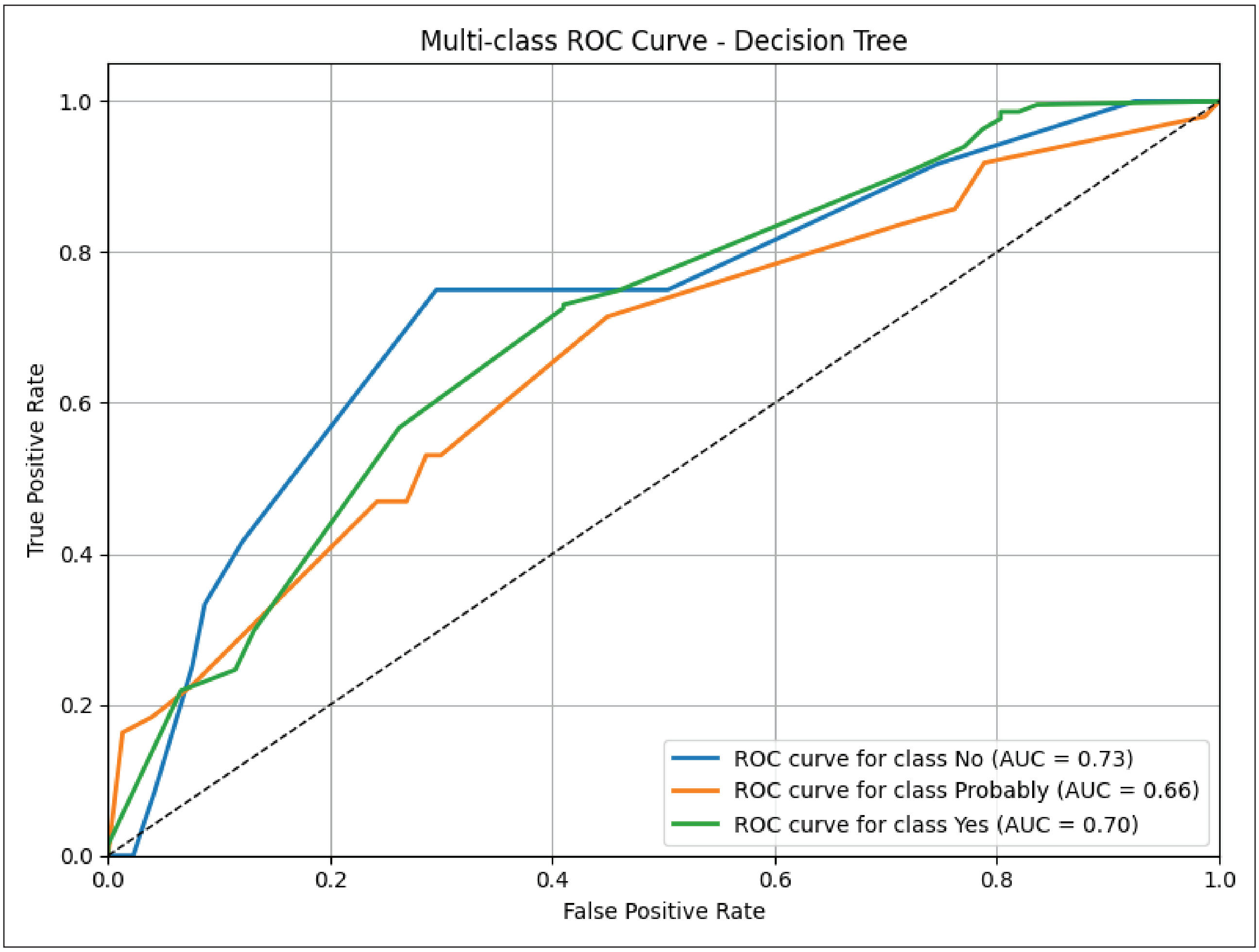

Figure 2. *ROC curves demonstrating the discriminative performance of the multiclass decision tree model.*

intelligence, but were strongly conditioned by contextual factors, particularly awareness of AI in research contexts, domains, and perceived institutional support. The placement of "awareness of AI in research contexts" as the root node highlights the importance of domain-specific exposure and familiarity. It has been demonstrated that domain literacy increases trust and intention to use AI tools in academic contexts [6]. Similarly, the use of AI tools has been reported to be negatively associated with perceived institutional confidence [14].

High awareness combined with strong institutional support resulted in high classification confidence for positive attitudes toward AI. This interaction suggests that institutions function not only as support systems but also as agents shaping the epistemic culture around AI. When both awareness and support were high, participants were consistently classified as having positive attitudes toward AI. This finding reinforces institutional readiness as a key pathway to technology acceptance and aligns with previous research showing that institutional guidance reduces ethical resistance and enhances researchers' confidence in AI use [10].

The decision tree also revealed consistent negative response patterns among researchers with low awareness and low support, with some decision rules yielding 100% classification confidence. These rigid patterns may reflect entrenched skepticism driven by concerns about ethical use, data trustworthiness, or fears that AI may replace scholarly roles [9]. In such cases, low exposure combined with limited institutional support may reinforce cognitive resistance and reluctance to adopt AI.

Although one rule predicted the "No" class with 100% confidence, this applied to a small subset of cases. Overall classification accuracy for the "No" class was 0%, likely due to class imbalance and limited representation. This highlights the risk of overfitting in decision paths derived from small subsets. Such rules may perform well under narrow conditions but fail to generalize, emphasizing the need for caution when interpreting high-confidence results in imbalanced datasets.

Pathways involving mixed levels of awareness and support were classified with moderate confidence, suggesting cognitive ambivalence or ethical uncertainty. This indicates that partial institutional efforts - such as introducing AI tools without sufficient training or ethical guidance - may result in hesitant rather than fully positive attitudes. These findings underscore the importance of integrated strategies that combine exposure, education, and ethical transparency.

ROC curve results further support this interpretation. Higher AUC scores for the "Yes" and "No" classes, compared to the "Probably" class, suggest increasing polarization in researchers' perceptions of AI. Strong institutional support or its absence appears to contribute to more definitive perceptions, while intermediate beliefs remain difficult to classify due to cognitive uncertainty and semantic ambiguity.

Methodologically, this study advances research by applying XAI approaches beyond descriptive statistics. The decision tree classifier illustrated in Figure 1 and summarized in Tables 2 and 3 maps distinct psychological and institutional profiles to perception outcomes. This approach not only supports socio-cognitive theories of technology acceptance but also provides interpretable tools for institutions to assess AI readiness and guide strategic implementation.

In summary, perceptions of AI in academic research reflect cognitive beliefs shaped by contextual signals, particularly awareness and institutional support. Institutions aiming to integrate AI must address both individual readiness and systemic reinforcement. Promoting AI literacy while establishing supportive institutional environments will be essential for sustainable and responsible AI adoption in the scientific community.

Strengths and limitations

This study has several strengths, including the use of a relatively large and multidisciplinary sample and an interpretable decision-tree model that provided transparent identification of factors influencing researchers' beliefs about AI in scientific research. The use of explainable machine-learning techniques also enhanced the practical relevance of the findings for institutional AI readiness assessment.

However, some limitations should be acknowledged. The cross-sectional design limits causal interpretation, while the convenience sampling approach may reduce generalizability and introduce selection bias. In addition, class imbalance, particularly the limited number of "No" responses, affected prediction performance for minority classes. External validation and *k*-fold cross-validation were also not performed.

Recommendation

Universities and research institutions are encouraged to strengthen AI awareness initiatives and provide structured institutional support to facilitate responsible AI integration in scientific research. Training, ethical guidance, technical infrastructure, and leadership support may improve researchers' confidence and readiness to engage with AI technologies. Future studies should include larger and more balanced datasets and external validation approaches to improve the generalizability of XAI models.

Conclusion

This study demonstrated that researchers' perceptions of AI in scientific research are strongly influenced by awareness of AI in research contexts and perceived institutional support. Using an interpretable decision-tree classification model, the findings showed that greater AI awareness and stronger institutional support were associated with more positive perceptions of AI integration in research.

The study highlights the importance of promoting AI literacy, institutional guidance, and supportive research environments to facilitate responsible AI adoption in academia. Furthermore, the use of explainable predictive modeling provides transparent tools that may assist institutions in assessing AI readiness and supporting evidence-based implementation strategies.

List of Abbreviations

AUC-ROC	Are Under th Receiver Operating Characteristic Curve
AI	Artificial ntelligence
TAM	Technology acceptance model
XAI	Explainable artificial intelligence

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Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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Consent to participate

Written informed consent was obtained from all participants before participation in the study.

Ethical approval

Ethical approval was given by the King Abdulaziz City for Science and Technology (KACST) on June 27, 2024 while IRB approval was approved by the Research Assist Institutional Review Board (IRB), Riyadh, Saudi Arabia (Approval No.

0311.01/2026). Written informed consent was obtained from all participants prior to data collection.

Author details

Roaa S. Bogdadi[1], Nahid A. Qushmaq[1], Marivel M. De Guzman[2] Rahaf Al Hasheem[3], Wijdan A. Baeshen[4], Sarah M. Aljuaid[4]

1. Research Department, King Abdullah Medical Complex, Jeddah, Saudi Arabia
2. Artificial Intelligence Department, KeyLife Electronics & At Pioneers Academy, Amman, Jordan
3. Research and Development Department, Research and Development for Research and Studies, Riyadh, Saudi Arabia
4. Research Department, Ministry of Health Branch in Jeddah, Jeddah, Saudi Arabia

Supplementary content (if any) is available online.

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