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ATTITUDES TOWARD AI ADOPTION IN BUSINESS: READINESS AS THE DETERMINANT OF VALUE CREATION ACROSS STUDENTS AND PRACTITIONERS

Dileta JATAUTAITĖ
Vilnius University
Saulėtekio av. 22., LT- 10225 Vilnius, Lithuania
E-mail: diletajatautaite@vm.vu.lt
ORCID ID: 0000-0003-4753-618X

Rūta ADAMONIENĖ
Mykolas Romeris University
Maironio str. 27, LT-44211 Kaunas, Lithuania
E-mail: rutadam@mruni.eu
ORCID ID: 0000-0002-7716-8093

Michail KAZIMIANEC
Vilnius University
Saulėtekio av. 22., LT- 10225 Vilnius, Lithuania
E-mail: michail.kazimianec@vm.vu.lt
ORCID ID: 0009-0002-0376-0593

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Abstract. *Artificial intelligence (AI) is increasingly integrated into business education and organizational practice, creating new opportunities for productivity improvement, decision support, process automation, and value creation. However, the availability of AI technologies does not automatically result in effective adoption or the realization of organizational value. Differences in users' knowledge, trust, perceived usefulness, ethical awareness, and organizational readiness may influence how AI is perceived and used in different contexts. This study examines attitudes toward AI adoption in business by investigating the relationships among perceived usefulness, AI literacy, trust in AI, ethical concerns, and behavioral intention, while also exploring differences between anticipated AI use among students and experienced AI use among business practitioners.*

A convergent mixed-methods research design was employed. The quantitative component was based on a structured survey of 140 business students at Vilnius University Business School. Data were collected through Google Forms using a five-point Likert scale and analyzed using descriptive statistics, reliability and validity assessment, and Partial Least Squares Structural Equation Modeling (PLS-SEM). The qualitative component consisted of semi-structured interviews with seven business practitioners who had experience using AI-based technologies in organizational settings. The interviews explored AI use in decision-making, organizational readiness, trust, risk perception, accountability, and changes in work processes. Quantitative and qualitative findings were subsequently integrated through methodological triangulation.

The quantitative results indicate that perceived usefulness has a significant positive relationship with behavioral intention to use AI ($\beta = 0.42$), while trust in AI also positively influences behavioral intention ($\beta = 0.29$). Ethical concerns demonstrate a significant negative relationship with behavioral intention ($\beta = -0.21$). AI literacy is positively associated with trust in AI ($\beta = 0.38$), while perceived usefulness also contributes positively to trust formation ($\beta = 0.35$). The structural model explains 63% of the variance in behavioral intention ($R^2 = 0.63$). The qualitative findings complement these results by demonstrating that practitioners assess AI adoption not only in terms of potential benefits but also through organizational readiness, accountability, task characteristics, trust, and implementation constraints.

The findings indicate that AI adoption should be understood as a multidimensional socio-technical process in which technological usefulness interacts with human capabilities, trust, ethical considerations, and organizational conditions. The study contributes to the AI adoption literature by connecting individual attitudes with contextual and organizational dimensions of AI use and by comparing anticipated and experienced perspectives on AI adoption.

Keywords: *Artificial intelligence, AI adoption, business education, organizational readiness, mixed-methods, technology acceptance, decision-making.*

Introduction

Artificial intelligence (AI) has become a core component of digital transformation strategies across business education and organizational environments. Its applications include process automation, predictive analytics, decision support systems, and customer engagement optimization. The rapid development of generative AI has further accelerated its diffusion, positioning AI as a strategic priority for organizations globally, particularly in Europe (Dwivedi et al., 2021; Huang & Rust, 2021; Brynjolfsson et al., 2024).

Despite this rapid expansion, empirical evidence shows that AI value realization remains highly heterogeneous across organizations and contexts. While some organizations achieve significant productivity gains, others struggle to integrate AI into decision-making processes effectively. This variation indicates that AI adoption depends not only on technological availability but also on human, organizational, and institutional factors (Benbya et al., 2020; Mikalef et al., 2022).

European policy frameworks emphasize trustworthy, ethical, and human-centered AI governance in high-risk socio-technical environments (European Commission, 2024; Floridi et al., 2018). As a result, AI adoption is increasingly shaped by regulatory compliance, ethical considerations, and organizational readiness structures.

Existing research mainly focuses on organizational determinants and individual acceptance models such as TAM and UTAUT. However, these frameworks have been extended in AI contexts due to limitations in explaining autonomy, uncertainty, and algorithmic decision-making (Venkatesh et al., 2003; Benbya et al., 2020; Dwivedi et al., 2021). Moreover, prior studies often examine students and practitioners separately, limiting comparative understanding of anticipated versus actual AI adoption behavior (Choung et al., 2023; Kaplan et al., 2021).

Therefore, this study addresses the lack of integrated empirical evidence on attitudes toward AI adoption among business students and practitioners. It aims to identify differences in perceived usefulness, trust, ethical concerns, and behavioral intention in AI use, contributing to a more comprehensive socio-technical understanding of AI adoption.

Research relevance

Artificial intelligence has become a strategic driver of digital transformation across business organizations and higher education. Although AI technologies are increasingly accessible, organizations continue to experience considerable variation in implementation success, indicating that technological availability alone is insufficient for creating organizational value. Understanding the determinants of AI adoption is therefore both theoretically and practically relevant. From a theoretical perspective, recent studies suggest that traditional technology acceptance models require extension to capture the socio-technical characteristics of AI systems, including trust, ethical concerns, and organizational readiness (Dwivedi et al., 2021; Benbya et al., 2020). From a practical perspective, identifying the factors that facilitate responsible AI adoption may help organizations, educators, and policymakers design more effective AI implementation strategies.

Research problem

Despite the rapid diffusion of artificial intelligence (AI) technologies in business environments, a persistent gap remains between technological availability and effective organizational adoption. Recent studies indicate that AI value creation depends not only on technological capability but also on human readiness, trust formation, AI literacy, and ethical evaluation mechanisms (Dwivedi et al., 2021; Huang & Rust, 2021).

This leads to a key unresolved question:

Why do positive individual attitudes toward AI not consistently translate into effective and responsible organizational adoption?

The breach becomes particularly visible when comparing user groups. Students typically demonstrate higher enthusiasm and stronger behavioral intentions toward AI adoption, whereas practitioners tend to demonstrate more cautious, risk-sensitive, and context-dependent evaluations of AI systems (Choung et al., 2023; Brynjolfsson et al., 2024).

Accordingly, the core research problem is formulated as follows:

There is insufficient integrated understanding of how AI readiness (AI literacy, trust, perceived usefulness, and ethical awareness) translates into behavioral intention and value creation across anticipated (students) and experienced (practitioners) AI adoption contexts.

In addition, existing literature does not adequately address the epistemic gap between abstract perceptions of AI and real-world implementation constraints within organizational environments.

Research object

The object of the research is artificial intelligence adoption in business contexts, focusing on the relationships among perceived usefulness, AI literacy, trust in AI, ethical concerns, and behavioral intention among business students and practitioners.

Research aim

The aim of this study is to investigate the determinants of artificial intelligence adoption in business by examining how perceived usefulness, AI literacy, trust in AI, and ethical concerns influence behavioral intention, and by comparing these relationships between business students and practitioners using a convergent mixed-methods approach.

The objectives of the study are to:

- review the theoretical and empirical literature on artificial intelligence adoption;
- identify the key cognitive, relational, capability, and ethical determinants of AI adoption;
- develop a conceptual model explaining behavioral intention to adopt AI;
- empirically examine the relationships among perceived usefulness, AI literacy, trust in AI, ethical concerns, and behavioral intention using PLS-SEM;
- compare AI adoption perceptions between business students and practitioners;
- integrate quantitative and qualitative findings to provide a comprehensive socio-technical explanation of AI adoption.

Research hypotheses

H1. Perceived usefulness has a positive effect on behavioral intention to use artificial intelligence.

H2. Trust in artificial intelligence positively influences behavioral intention.

H3. Ethical concerns negatively influence behavioral intention.

H4. AI literacy positively influences trust in artificial intelligence.

H5. Perceived usefulness positively influences trust in artificial intelligence.

H6. The relationships among AI adoption constructs differ between business students and practitioners.

Research methods

The study employs a convergent mixed-methods research design combining quantitative and qualitative approaches. The quantitative component was used to examine the relationships among the main AI adoption constructs, while the qualitative component was designed to provide contextual and experiential insights into AI use in organizational environments. The two strands were analyzed separately and subsequently integrated through methodological triangulation.

Quantitative research design

The quantitative phase involved a structured questionnaire administered to 140 business students at Vilnius University Business School during the autumn semester of 2025. The questionnaire was distributed electronically through Google Forms. Participation was voluntary and respondents were informed about the academic purpose of the study.

The questionnaire used a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The measurement instrument covered the following constructs:

• Perceived Usefulness (PU), referring to respondents' perceptions of the benefits and performance-enhancing potential of AI;

• Perceived Ease of Use (PEOU), referring to the perceived simplicity and effort required to use AI systems;

• Trust in Artificial Intelligence (TR), referring to confidence in the reliability and usefulness of AI-generated outputs;

• AI Literacy (AIL), referring to respondents' knowledge and ability to understand and use AI-based tools;

• Ethical Concerns (EC), referring to concerns related to bias, privacy, misuse, transparency, accountability, and over-reliance on AI;

• Behavioral Intention (BI), referring to respondents' intention to use AI in future academic and professional activities.

The quantitative data were first examined using descriptive statistics to identify the central tendency and variability of the measured constructs. Internal consistency was assessed using Cronbach's alpha and Composite Reliability (CR). Convergent validity was assessed using Average Variance Extracted (AVE). Partial Least Squares Structural Equation Modeling (PLS-SEM) was subsequently applied to examine the hypothesized relationships among the constructs.

The structural model was evaluated by examining standardized path coefficients (β), t-values, statistical significance, and the coefficient of determination (R^2). Bootstrapping

procedures available in SmartPLS were used to assess the statistical significance of the estimated relationships. The analysis focused on five hypothesized structural relationships: perceived usefulness and behavioral intention (H1), trust and behavioral intention (H2), ethical concerns and behavioral intention (H3), AI literacy and trust (H4), and perceived usefulness and trust (H5).

Qualitative research design

The qualitative phase involved semi-structured interviews with seven business practitioners selected through purposive sampling. Participants were selected based on their professional experience with AI-based technologies in organizational contexts. The participants represented different professional functions, including business analysis, digital transformation, marketing, operations, and entrepreneurship.

The interviews lasted approximately 60–90 minutes and followed a semi-structured interview protocol. This format provided a consistent thematic structure while allowing participants to elaborate on their individual experiences. The interview protocol addressed six main areas: (1) current use of AI in organizations; (2) AI-supported decision-making; (3) organizational readiness for AI adoption; (4) trust and reliability of AI outputs; (5) perceived risks, ethical concerns, and accountability; and (6) changes in work processes and workforce roles.

The interviews were audio-recorded and transcribed for subsequent analysis. The qualitative data were analyzed using thematic analysis following the six-phase approach proposed by Braun and Clarke. The analysis involved familiarization with the transcripts, generation of initial codes, identification of potential themes, review of themes, definition and naming of themes, and final interpretation.

Five major themes were identified: AI as a decision-support tool rather than an autonomous decision-maker; conditional trust in AI systems; organizational readiness gaps; risk and accountability concerns; and workforce transformation dynamics.

Following the separate analysis of quantitative and qualitative data, the findings were integrated through methodological triangulation. The purpose of integration was not to statistically compare the two samples, as the quantitative and qualitative components differ in design and sample size, but to identify areas of convergence and divergence in perceptions of AI adoption.

The integration focused on four dimensions: perceived value and usefulness of AI, trust, readiness, and decision-making. The student findings were interpreted as evidence of anticipated AI adoption, whereas the practitioner interviews provided evidence of experienced AI use within organizational contexts.

This approach enables the study to connect individual-level attitudes with organizational and contextual factors and to identify how AI adoption may be interpreted differently depending on users' experience and organizational environment.

Literature review

Research on technology acceptance has been fundamentally shaped by cognitive decision models explaining user behavior through perceived usefulness and effort expectations. The Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) remain the dominant theoretical foundations in information systems research.

However, recent meta-analytic and systematic review evidence indicates that these models demonstrate only moderate explanatory power in artificial intelligence contexts. AI systems introduce autonomy, unpredictability, and probabilistic decision-making that extend beyond traditional information systems logic (Dwivedi et al., 2021; Zhang et al., 2023). As a result, AI adoption research increasingly incorporates socio-technical and psychological constructs, particularly trust, risk perception, and ethical evaluation (Benbya et al., 2020; Huang & Rust, 2021).

Artificial intelligence fundamentally transforms human–technology interaction by enabling systems to perform cognitive, adaptive, and decision-support functions. This transformation shifts AI from a passive tool to an active socio-technical agent embedded in organizational decision processes.

Dwivedi et al. (2021) argue that AI introduces a shift from human–computer interaction to human–AI collaboration, requiring continuous reinterpretation of system outputs. Similarly, Raisch and Krakowski (2021) conceptualize AI adoption as an automation–augmentation paradox, requiring a balance between efficiency gains and human oversight.

Meta-analytic evidence further indicates that successful AI adoption depends not only on technical capability but also on organizational alignment, data governance, and absorptive capacity (Mikalef et al., 2022).

Empirical meta-analytical evidence on AI adoption drivers

Meta-analyses consistently identify a stable set of determinants influencing AI adoption across contexts. Perceived usefulness, trust, and perceived risk emerge as the strongest predictors of behavioral intention across industries (Gursoy et al., 2023; Li et al., 2023). Furthermore, trust has been shown to mediate the relationship between cognitive evaluations and behavioral intention in AI systems (Kaplan et al., 2021).

Across studies, four dominant patterns are observed:

- Perceived usefulness is the strongest positive determinant of behavioral intention;
- Trust operates as a central mediating mechanism;
- Perceived risk consistently reduces adoption intention;
- AI literacy influences intention indirectly through trust and self-efficacy.

These findings indicate that AI adoption cannot be explained solely through utilitarian evaluations, but instead reflects a layered cognitive–affective–risk structure.

Trust in artificial intelligence systems

Trust has become a central construct in AI adoption research due to the opacity, autonomy, and non-deterministic nature of AI systems. Unlike traditional technologies, AI outputs often lack full interpretability, increasing perceived uncertainty.

Kaplan et al. (2021) demonstrate that trust in AI is shaped by system performance, transparency, and contextual reliability. Similarly, Shin (2021) shows that explainability significantly enhances trust formation.

Trust is a multidimensional construct involving cognitive, affective, and contextual dimensions (Bach et al., 2023). Empirical studies also highlight algorithm aversion, where users reject algorithmic recommendations even when they outperform human judgment (Dietvorst et al., 2018; Longoni et al., 2022).

Ethical concerns, risk perception, and governance constraints

Ethical concerns have become a core determinant of AI adoption, particularly in regulated environments. Issues related to bias, accountability, privacy, and transparency significantly reduce behavioral intention.

Perceived risk consistently operates as a structural barrier to adoption and often outweighs perceived benefits in high-uncertainty contexts (Zhang et al., 2023; Leschanowsky et al., 2024). In parallel, regulatory frameworks such as the European Union AI Act institutionalize ethical constraints in AI deployment (European Commission, 2024).

These findings demonstrate that AI adoption is not solely behavioral but deeply embedded in institutional and regulatory structures.

Organizational readiness and AI capability development

Organizational readiness is a key determinant of AI value realization. It reflects digital infrastructure maturity, data governance quality, leadership capability, and AI-related competencies.

Recent research conceptualizes AI adoption as capability accumulation rather than discrete technology adoption (Mikalef et al., 2022). High-performing organizations align technical systems with managerial capabilities and absorptive capacity.

AI literacy and human capability factors

AI literacy plays a critical role in AI adoption, primarily through indirect effects on trust formation and self-efficacy.

Higher AI literacy improves trust calibration and enhances the ability to interpret AI outputs (Yu et al., 2023). However, literacy alone does not directly predict behavioral intention; instead, it operates through mediating cognitive mechanisms such as trust and perceived control (Sallam, 2023).

Comparative perspectives: students vs practitioners

Empirical studies consistently reveal systematic differences between anticipated and actual AI adoption contexts.

Students tend to demonstrate higher perceived usefulness and stronger behavioral intentions, while exhibiting lower contextual risk awareness. In contrast, practitioners demonstrate higher risk sensitivity, conditional trust, and stronger awareness of organizational constraints (Choung et al., 2023; Brynjolfsson et al., 2024).

This reflects a persistent intention–behavior gap in technology adoption research.

Synthesis and conceptual gap

Despite substantial progress in AI adoption research, three key gaps remain.

First, existing models remain overly cognitive and insufficiently account for socio-technical complexity in AI systems.

Second, trust, ethics, and readiness are often studied in isolation rather than as an integrated system.

Third, comparative analyses between students and practitioners remain limited, restricting understanding of adoption evolution across experience levels.

To address these gaps, this study conceptualizes AI adoption as a readiness-dependent socio-technical system integrating:

- Cognitive factors (usefulness, ease of use);
- Capability factors (AI literacy, readiness);
- Relational factors (trust);
- Normative factors (ethics and risk perception).

This framework aligns with recent calls for multi-level AI adoption models in organizational research (Dwivedi et al., 2021; Mikalef et al., 2022).

Research gap and conceptual positioning

Despite rapid growth in AI adoption literature, several gaps remain.

First, established technology acceptance models such as TAM and UTAUT provide valuable explanatory power; however, their applicability becomes more limited in AI contexts characterized by autonomy, uncertainty, and ethical complexity (Dwivedi et al., 2021; Zhang et al., 2023). This limitation reflects a broader shift from deterministic information systems toward probabilistic, adaptive AI systems, where user interpretation and contextual judgment become central determinants of adoption.

Second, prior research has largely examined individual, organizational, and ethical dimensions separately, resulting in a partially fragmented understanding of AI adoption as a socio-technical phenomenon (Benbya et al., 2020; Huang & Rust, 2021). Consequently, integrated multi-level explanatory frameworks remain underdeveloped, particularly those linking cognitive, relational, capability, and normative dimensions within a single model.

Third, comparative empirical evidence between students and practitioners remains limited, despite its theoretical importance for understanding how AI perceptions evolve from anticipated to actual adoption contexts (Choung et al., 2023). This restricts understanding of the intention–behavior transition in AI-enabled environments and limits insights into experiential learning effects.

Finally, AI readiness is still an emerging construct, often operationalized through separate dimensions such as digital skills, trust, or infrastructure, rather than as an integrated capability perspective (Mikalef et al., 2022). This fragmentation limits theoretical consolidation and reduces the explanatory coherence of AI adoption models.

This study addresses these limitations by positioning AI adoption as a socio-technical and capability-based process integrating cognitive, relational, capability, and normative dimensions into a unified analytical framework.

Empirical study design

This study applies a convergent mixed-methods design, in which quantitative and qualitative strands are collected and analyzed in parallel and subsequently integrated.

The quantitative component examines structural relationships between AI adoption constructs using survey data from business students. The survey was administered via Google Forms, ensuring standardized and transparent data collection within an academic research setting. Participants (N = 140) were students of Vilnius University Business School, representing a relatively homogeneous demographic group. This homogeneity strengthens

internal consistency and reduces variability related to demographic heterogeneity within the sample. The data collection was conducted in autumn 2025.

The qualitative component explores contextual interpretations of AI use in organizational environments based on semi-structured interviews with seven business practitioners. These participants represent experienced users of AI technologies in managerial and operational contexts, enabling the exploration of real-world implementation constraints and organizational decision-making dynamics.

The integration of both strands enables methodological triangulation between behavioral intention and real-world implementation perspectives, allowing systematic comparison between anticipated (student) and experienced (practitioner) AI adoption contexts.

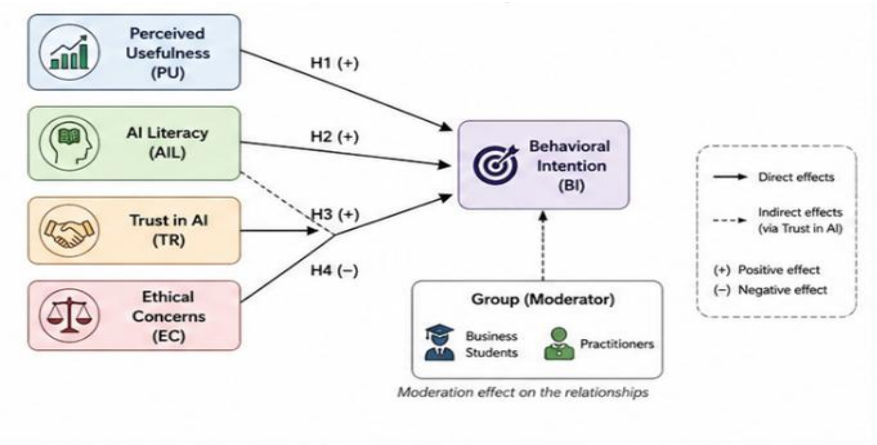


Figure 1: Research Design Model (Convergent Mixed-Methods Framework)
Source: Compiled by the author based on the empirical research (2025).

Conceptual model and hypotheses

Figure 1 presents the theoretical foundation of the study and the hypothesized relationships between constructs. The model integrates:

- Perceived Usefulness (PU – perceived benefits of AI in performance);
- AI Literacy (AIL – knowledge and ability to use AI tools);
- Trust in Artificial Intelligence (TR – confidence in AI systems and outputs);
- Ethical Concerns (EC – perceived risks such as bias, privacy, and misuse);
- Behavioral Intention (BI – intention to use AI in business contexts);
- Group effect (Students vs Practitioners as a moderating variable).

The model specifies both direct effects (H1–H4) and a moderating effect of group membership, forming the theoretical basis for empirical testing using Partial Least Squares Structural Equation Modeling (PLS-SEM).

Research context and sampling strategy

The quantitative phase is based on survey data collected from 140 business students enrolled at Vilnius University Business School (VU BS), Vilnius University, Lithuania. The sample includes Lithuanian and international students in Bachelor's and Master's programmes in Business Administration, International Business, and Management.

A combination of convenience and purposive sampling was applied. Convenience sampling refers to the selection of readily accessible participants, while purposive sampling ensures inclusion of respondents with prior exposure to artificial intelligence tools relevant to the study context.

The inclusion criterion was exposure to AI-based tools such as generative AI systems (e.g., ChatGPT), business analytics platforms, and digital decision-support systems.

The student sample represents a relatively homogeneous academic population, which enhances internal consistency of responses but limits external generalizability.

Data collection was conducted via Google Forms during the autumn semester of 2025, ensuring standardized and traceable survey administration.

The student group represents future labour market participants, and their responses reflect anticipated AI adoption behaviour, early-stage trust formation, and perceived readiness for AI-enabled environments.

Qualitative phase

The qualitative phase includes seven business practitioners selected through purposive sampling based on their professional experience with artificial intelligence technologies in organizational contexts.

Participants include business analysts, digital transformation specialists, marketing managers, operations managers, and startup founders. All participants actively use AI-based tools in their daily work for decision-making support, process automation, data analysis, and marketing optimisation.

This group provides insights into real-world organizational constraints, implementation challenges, and contextual AI adoption processes.

Data were collected through semi-structured interviews, enabling in-depth exploration of practitioner experiences and contextual decision-making dynamics.

Table 1. Sample Overview
Source: Compiled by the author)

Research Phase	Population	Sample Size	Method	Purpose
Quantitative	Business students (VU BS)	140	Survey (Google Forms)	Statistical modelling of AI adoption
Qualitative	Business practitioners	7	Semi-structured interviews	Contextual and experiential analysis

Data collection procedures

The empirical research process consists of three sequential but integrated phases: quantitative data collection, qualitative data collection, and integration of findings.

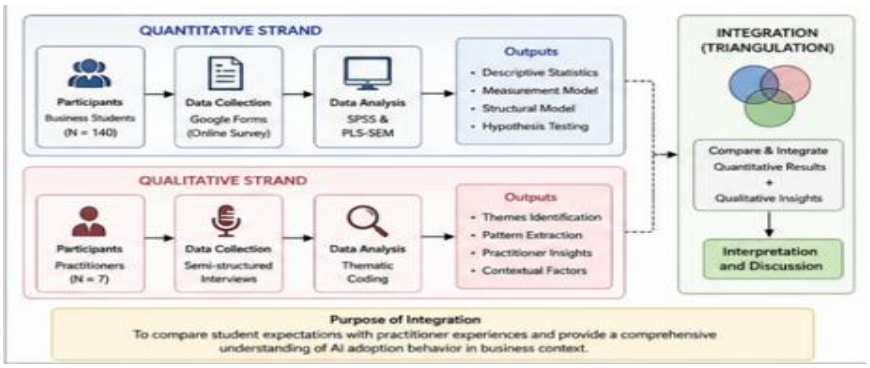


Figure 2: Research Design and Data Collection Process
Source: Compiled by the author based on the empirical research (2025).

Data collection and workflow

Figure 2 illustrates the overall research workflow, integrating quantitative and qualitative strands within a mixed-methods design. The quantitative strand comprises a survey of N = 140 business students using a 5-point Likert scale, followed by statistical analyses including descriptive statistics, reliability assessment, measurement model testing, PLS-SEM, and hypothesis testing. The qualitative strand comprises N = 7 business practitioners and is based on semi-structured interviews, analyzed through thematic coding and pattern identification. In the final integration phase, both datasets are triangulated to identify convergence and divergence between student and practitioner perspectives, enabling a unified interpretation of attitudes toward AI adoption.

Quantitative data collection

Quantitative data were collected using a structured online questionnaire distributed via university communication channels, lecture groups, and student networks. A 5-point Likert scale was applied (1 = strongly disagree, 5 = strongly agree).

The survey measured six constructs:

- Perceived Usefulness (PU) – perceived performance benefits of AI;
- Perceived Ease of Use (PEOU) – perceived ease of using AI systems;
- Trust in Artificial Intelligence (TR) – confidence in AI outputs;
- AI Literacy (AIL) – ability to understand and use AI tools;
- Ethical Concerns (EC) – concerns regarding bias, privacy, misuse, and over-reliance;
- Behavioral Intention (BI) – intention to use AI in future academic or professional activities.

Qualitative data collection

Qualitative data were collected through semi-structured interviews lasting 60–90 minutes with business practitioners. Semi-structured interviews enable flexible yet focused exploration of participants' experiences while maintaining thematic consistency across interviews.

The discussion covered six thematic areas: AI use in organizations, decision-making processes, organizational readiness, trust formation, risk perception, and workforce transformation.

All interviews were audio-recorded and transcribed verbatim for analysis.

Table 2. Data Collection Instruments
Source: Compiled by the author

Method	Instrument	Constructs / Focus	Output
Survey	Structured questionnaire (Likert scale)	PU, PEOU, TR, AIL, EC, BI	Quantitative dataset
Interviews	Semi-structured protocol	Trust, risk, readiness, decision-making	Qualitative transcripts

Data analysis procedures

Quantitative data were analyzed using SPSS (Statistical Package for the Social Sciences) and SmartPLS (Partial Least Squares Structural Equation Modeling software).

The analysis followed three sequential stages:

First, descriptive statistics were used to summarize the central tendency and variability of constructs.

Second, reliability and validity were assessed using:

- Cronbach's alpha (internal consistency reliability);
- Composite Reliability (CR, construct reliability);
- Average Variance Extracted (AVE, convergent validity).

Third, Structural Equation Modeling using Partial Least Squares (PLS-SEM) was applied to test hypothesized relationships among constructs and to assess the model's explanatory power (R^2).

In addition, multi-group analysis was conducted to examine differences between Lithuanian and international students.

Qualitative analysis

Qualitative data were analyzed using thematic analysis following the six-phase framework proposed by Braun and Clarke. The process included data familiarization, initial coding, theme generation, theme review, theme definition, and final interpretation.

Five main themes emerged:

- AI as a decision-support tool rather than an autonomous system;
- Conditional trust in AI systems;
- Organizational readiness gaps;
- Risk and accountability concerns;
- Workforce transformation dynamics.

Table 3. Data Analysis Methods
Source: Compiled by the author

Phase	Method	Tool	Output
Quantitative	Descriptive analysis	SPSS	Summary statistics
Quantitative	Structural modeling	SmartPLS	Path relationships
Qualitative	Thematic analysis	Manual coding	Conceptual themes

Integration strategy

The integration of quantitative and qualitative findings was conducted using triangulation. Triangulation refers to the process of comparing and combining results from multiple data sources to enhance validity, depth, and interpretative robustness.

Three key dimensions were compared: AI perception, trust, readiness, and decision-making logic.

Students demonstrated an opportunity-driven perspective, viewing AI as a tool for future performance improvement. In contrast, practitioners demonstrated a risk-sensitive and context-dependent perspective shaped by organizational constraints, accountability structures, and implementation realities.

Table 4. Triangulation of Findings
Source: Compiled by the author

Dimension	Business Students	Practitioners
AI perception	Future-oriented opportunity	Operational risk and constraint
Trust	Moderate to high (abstract)	Conditional and task-dependent
Readiness	Theoretical readiness	Organizational readiness
Decision logic	Intention-based	Context-based

Results

Descriptive analysis shows that business students exhibit generally positive attitudes toward artificial intelligence adoption. The highest mean values are observed in Behavioral Intention (BI = 4.46) and Perceived Usefulness (PU = 4.41), indicating a strong willingness to adopt AI in future professional contexts.

Ethical concerns (EC = 3.95) remain relatively high, suggesting that students simultaneously perceive AI as beneficial and potentially risky.

Table 5. Descriptive Statistics of Constructs
Source: Compiled by the author

Construct	Mean	Standard Deviation	Interpretation
Perceived Usefulness (PU)	4.41	0.62	Very high
AI Literacy (AIL)	4.08	0.70	High
Trust in AI (TR)	3.82	0.73	Moderate
Ethical Concerns (EC)	3.95	0.77	High
Behavioral Intention (BI)	4.46	0.59	Very high

Measurement Model Results

Measurement model evaluation confirmed the strong reliability and validity of all constructs. All Cronbach's alpha values exceeded the recommended threshold of 0.70, indicating acceptable internal consistency.

Composite reliability values exceeded 0.85, confirming construct reliability, while AVE values exceeded 0.50, confirming convergent validity.

Table 6. Measurement Model Quality
Source: Compiled by the author

Construct	Cronbach's Alpha	Composite Reliability	AVE
PU	0.88	0.91	0.72
TR	0.86	0.90	0.70
AIL	0.84	0.88	0.69
EC	0.83	0.87	0.66
BI	0.89	0.92	0.75

Structural Model Results (PLS-SEM)

The structural model confirms statistically significant relationships among all hypothesized constructs. Perceived usefulness and AI literacy emerge as the strongest predictors of behavioral intention, while ethical concerns exert a significant negative effect.

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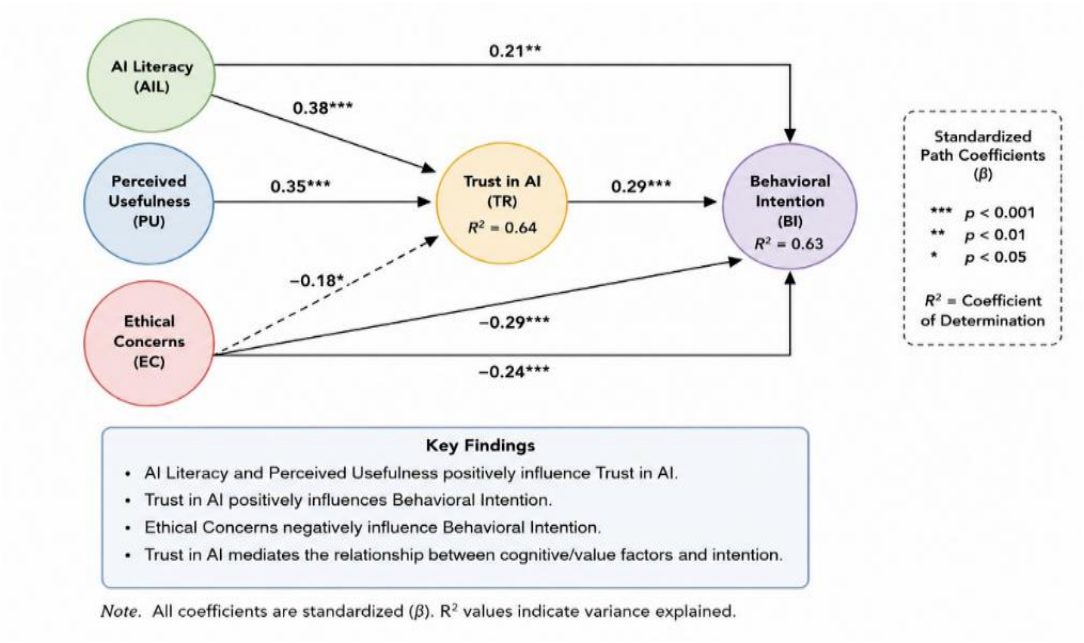


Figure 3. Structural Model Results (PLS-SEM)
Source: Compiled by the author based on the empirical research (2025).

Figure 3 presents the structural model estimated using Partial Least Squares Structural Equation Modeling (PLS-SEM). The model illustrates the statistically significant relationships among the study constructs, including standardized path coefficients (β) and the explained variance (R^2) for Behavioral Intention.

Perceived usefulness has the strongest positive direct effect on behavioral intention (β = 0.42), followed by trust in AI (β = 0.29), while ethical concerns negatively influence behavioral intention (β = –0.21). In addition, AI literacy significantly affects trust in AI (β = 0.38), and perceived usefulness also contributes to trust formation (β = 0.35).

The model explains 63% of the variance in behavioral intention (R^2 = 0.63), indicating substantial explanatory and predictive power.

Importantly, AI readiness emerges as the most comprehensive predictor of behavioral intention, suggesting that AI adoption is primarily driven by readiness-related capabilities rather than isolated cognitive evaluations.

Table 7. Structural Model Results
Source: Compiled by the author

Path Relationship	Path Coefficient (β)	t-value	Significance
PU → BI	0.42	6.21	Significant
TR → BI	0.29	4.02	Significant
EC → BI	-0.21	3.45	Significant
AIL → TR	0.38	5.11	Significant
PU → TR	0.35	4.89	Significant

Model explanatory power: $R^2 = 0.63$ (Behavioral Intention)

The findings suggest that AI adoption should be interpreted in relation to readiness-related conditions, including AI literacy, trust, ethical awareness, and organizational context. Rather than representing a single statistically tested construct in the present PLS-SEM model, AI readiness is conceptualized as a broader socio-technical condition that may facilitate or constrain AI adoption. The quantitative findings demonstrate the importance of individual-level factors such as perceived usefulness, trust, and AI literacy, while the qualitative findings further demonstrate the importance of organizational readiness, accountability, and implementation conditions.

Structural Model Interpretation

PLS-SEM results confirm that perceived usefulness, trust in AI, AI literacy, and ethical concerns all significantly influence behavioral intention. AI readiness demonstrates the strongest overall explanatory contribution, indicating that AI adoption is not solely driven by cognitive perceptions (such as usefulness), but is better explained as a readiness-dependent socio-technical process combining capability, trust, and contextual constraints.

Group Comparison Results

The comparative analysis reveals differences in how business students and practitioners perceive and interpret AI adoption. Because the two components of the study were based on different methodological approaches and sample sizes, the comparison is interpretative rather than a statistical test of group differences.

Figure 4 integrates findings from both the quantitative and qualitative phases using methodological triangulation. It compares students and practitioners across four key dimensions: perceived usefulness, trust in AI, ethical concerns, and organizational readiness.

Students predominantly view AI as an opportunity-enhancing tool, expressing high behavioral intention and positive expectations regarding future performance improvements. In contrast, practitioners emphasize organizational constraints, accountability structures, and context-dependent trust shaped by practical experience.

The results indicate both convergence and divergence between the two perspectives. While both groups recognize the potential value of AI, practitioners place greater emphasis on organizational readiness, risk, accountability, and implementation conditions, whereas students primarily express expectations concerning usefulness and future application. These complementary perspectives reinforce the value of integrating quantitative and qualitative evidence when examining AI adoption.

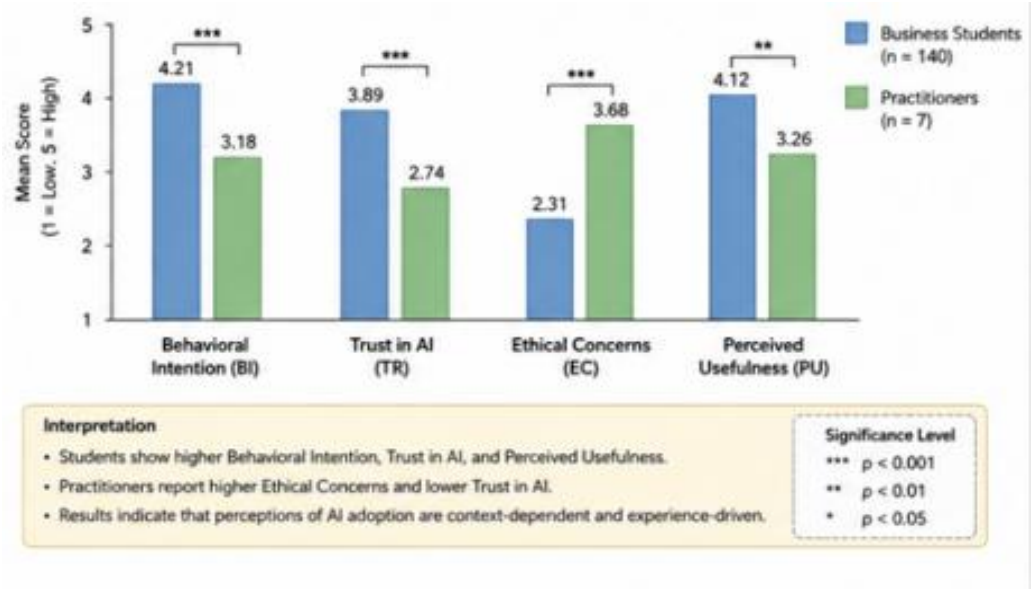


Figure 4: Comparison of AI Adoption Attitudes Between Students and Practitioners
Source: Compiled by the author based on the empirical research (2025).

Results

The integrated analysis demonstrates that both groups recognize the strategic value of artificial intelligence in business contexts; however, their interpretations differ in emphasis and underlying logic.

Students predominantly associate AI with future-oriented opportunities, innovation potential, and performance enhancement. In contrast, practitioners evaluate AI through an implementation-oriented lens, emphasizing organizational constraints, governance structures, and accountability mechanisms.

These complementary perspectives indicate that AI adoption is not solely an individual cognitive decision but is embedded in broader organizational, institutional, and experiential contexts shaped by trust and readiness conditions.

Table 8. Group Comparison Results
Source: Compiled by the author

Construct	Lithuanian Students	International Students
Perceived Usefulness	Higher	Slightly higher
Trust in AI	Moderate	Higher
AI Literacy	Moderate	Higher
Ethical Concerns	Higher	Slightly lower
Behavioral Intention	High	Higher

Discussion

Overall, the results confirm that artificial intelligence adoption is a multidimensional socio-technical phenomenon shaped by cognitive evaluations, trust mechanisms, ethical awareness, and organizational readiness.

The observed divergence between students and practitioners further confirms that AI adoption cannot be conceptualized as a linear technological diffusion process. Instead, it reflects a readiness-dependent system in which perceptions are continuously shaped by contextual exposure, institutional constraints, and experiential learning.

The findings indicate that artificial intelligence adoption in business contexts is best understood as a socio-technical phenomenon rather than a purely cognitive decision process. Perceived usefulness remains the strongest direct predictor of behavioral intention, complemented by trust in AI, AI literacy, and ethical concerns. This confirms that AI adoption outcomes depend on an interplay between cognitive evaluations, capability factors, and normative considerations.

A key theoretical contribution of this study is the identification of AI readiness as an integrative construct combining individual competence and organizational capability. The results suggest that AI readiness not only directly influences behavioral intention but also strengthens the relationships between cognitive perceptions and adoption outcomes, highlighting its role as a higher-order enabling condition.

The comparative analysis reveals systematic differences between user groups. Students tend to emphasize perceived usefulness and future-oriented benefits of AI, reflecting an opportunity-driven perspective. In contrast, practitioners interpret AI adoption through the lens of organizational constraints, accountability, and implementation feasibility, reflecting experience-based and context-dependent evaluations. These differences support the view that AI adoption evolves with practical exposure and organizational embedding.

Trust in AI functions as a key mediating mechanism, linking AI literacy to behavioral intention. Higher levels of AI literacy improve users' ability to interpret and evaluate AI outputs, but adoption is contingent on the extent to which users trust system reliability and interpretability.

Ethical concerns consistently reduce behavioral intention, confirming that issues related to bias, transparency, and accountability remain central barriers to AI adoption. This highlights the importance of regulatory frameworks in shaping responsible AI deployment.

Overall, the results extend established technology acceptance models by demonstrating that AI adoption is driven not only by perceived usefulness but also by readiness, trust, and ethical evaluation. The findings support a multi-dimensional framework in which AI adoption is shaped by the interaction of cognitive, capability, relational, and normative factors.

Limitations

Several limitations of this study should be acknowledged.

First, the quantitative sample is limited to business students from a single university, which constrains the generalizability of the findings. Future research should employ multi-institutional and cross-country samples to improve external validity.

Second, the qualitative sample consists of a small number of practitioners, which allows for in-depth insights but limits the representativeness of findings across industries and organizational contexts.

Third, reliance on self-reported data may introduce common method bias and social desirability effects, particularly in relation to behavioral intention and perceived competence.

Fourth, the cross-sectional research design does not allow for the examination of longitudinal dynamics, especially the transition from intention to actual AI usage behavior over time.

Finally, although the convergent mixed-methods design enables triangulation of findings, the integration of quantitative and qualitative results remains interpretative rather than statistical, which limits causal inference across research strands.

Conclusion

This study examined artificial intelligence adoption in business contexts using a convergent mixed-methods design that integrates quantitative data from business students and qualitative insights from practitioners. The findings confirm that AI adoption is a multidimensional socio-technical phenomenon shaped by cognitive, relational, capability, and ethical factors.

A key insight is that classical technology acceptance models are insufficient to fully explain AI adoption, as their explanatory power depends on trust formation processes and organizational readiness conditions. AI adoption, therefore, extends beyond cognitive evaluations of technology and must be understood as a context-dependent process embedded within organizational and institutional environments.

The study contributes to theory in three main ways. First, it extends established acceptance frameworks (TAM and UTAUT) by embedding them within a socio-technical perspective that accounts for interactions between individual capabilities and organizational structures. Second, it introduces AI readiness as an integrative construct linking individual perceptions with organizational constraints. Third, it demonstrates systematic differences in AI adoption between students and practitioners, reflecting variation in experience, risk perception, and contextual exposure.

From a practical perspective, the findings suggest that effective AI implementation requires more than technological deployment. Organizations need to invest in AI literacy development, trust-building mechanisms, and ethical governance structures to support meaningful integration of AI into decision-making processes. Educational institutions also play a critical role in aligning AI-related competencies with evolving organizational needs.

From a policy perspective, the results highlight the importance of ethical governance frameworks such as the European Union Artificial Intelligence Act in shaping responsible AI adoption. This underscores that AI adoption is simultaneously a technological, organizational, and regulatory challenge.

Future research should investigate longitudinal adoption dynamics to better understand the transition from intention to actual use. Further studies should also extend cross-cultural and cross-industry comparisons to capture contextual variability in AI readiness, while refining the AI readiness construct to improve its measurement validity and comparability.

Overall, this study positions AI adoption as a readiness-dependent socio-technical process in which cognitive, organizational, and ethical dimensions jointly determine how AI creates value across different user groups and contexts.

References

1. Bach, T. A., Khan, A., Hallock, H., Beltrão, G., & Sousa, S. (2023). A systematic literature review of user trust in AI-enabled systems: An HCI perspective. *arXiv preprint*. https://doi.org/10.48550/arXiv.2304.08795
2. Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Artificial intelligence in organizations: Current state and future opportunities. *MIS Quarterly Executive, 19*(4), 1–16.

3. Brynjolfsson, E., Li, D., & Raymond, L. R. (2024). Generative AI at work. *NBER Working Paper No. 31161*. https://www.nber.org/papers/w31161
4. Choung, H., David, P., & Ross, A. (2023). Trust in AI and human–AI collaboration: A systematic review. *Computers in Human Behavior, 139*, 107545. https://doi.org/10.1016/j.chb.2022.107545
5. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008
6. Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General, 147*(11), 1702–1717. https://doi.org/10.1037/xge0000462
7. Dwivedi, Y. K., et al. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
8. Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2023). Consumer acceptance of AI devices in service encounters. *International Journal of Hospitality Management, 113*, 103466. https://doi.org/10.1016/j.ijhm.2023.103466
9. Huang, M. H., & Rust, R. T. (2021). Artificial intelligence in service. *Journal of Service Research, 24*(1), 3–14. https://doi.org/10.1177/1094670520902266
10. Kaplan, A. D., Kessler, T. T., Brill, J. C., & Hancock, P. A. (2021). Trust in artificial intelligence: Meta-analytic findings. *Human Factors, 65*(2), 377–402. https://doi.org/10.1177/00187208211013988
11. Leschanowsky, A., Rech, S., Popp, B., & Bäckström, T. (2024). Evaluating privacy, security, and trust perceptions in conversational AI: A systematic review. *arXiv preprint*. https://doi.org/10.48550/arXiv.2406.09037
12. Li, B., Chen, Y., Liu, L., & Zheng, B. (2023). Users' intention to adopt AI-based chatbots: A meta-analysis. *The Service Industries Journal, 43*(15–16), 1117–1139. https://doi.org/10.1080/02642069.2023.2217756
13. Longoni, C., Bonezzi, A., & Morewedge, C. K. (2022). Resistance to medical artificial intelligence. *Journal of Consumer Research, 49*(4), 681–703. https://doi.org/10.1093/jcr/ucab045
14. Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. A. (2022). Big data analytics capabilities and firm performance. *Information & Management, 59*(2), 103291. https://doi.org/10.1016/j.im.2021.103291
15. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072
16. Shin, D. (2021). The effects of explainability and transparency on trust in AI systems. *Computers in Human Behavior, 114*, 106526. https://doi.org/10.1016/j.chb.2020.106526
17. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.
18. Zhang, B., Dafoe, A., & HAI Group. (2023). Artificial intelligence adoption and trust: A systematic review and meta-analysis. *Technological Forecasting & Social Change, 190*, 122381. https://doi.org/10.1016/j.techfore.2023.122381



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