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Artificial Intelligence Applications in Business, Education and Society

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Abstract - Over the past decade, artificial intelligence (AI) has moved from research laboratories into everyday practice. Companies use it to forecast demand, personalise offers and automate routine work, while schools and universities apply it to adaptive tutoring, immediate feedback and learning analytics. Public institutions and communities draw on it in healthcare, civic services, transport and safety. This paper examines AI applications in three connected domains (business, education and society) and asks which benefits, risks and enabling conditions recur across all of them. The study follows a mixed-methods design: a systematic review of peer-reviewed literature published mainly between 2017 and 2024, a structured questionnaire for business professionals, teachers, students and members of the public, and semi-structured interviews that deepen the survey findings.

The expected contribution is an integrated framework that links the drivers of AI adoption (perceived usefulness, organisational readiness, digital skills and trust) to outcomes in productivity, quality of learning and social wellbeing. The framework also accounts for moderating concerns such as bias, privacy, job displacement and academic integrity. The central argument is that the value AI creates depends more on governance, human capability and ethical design than on the technology itself. The findings are intended to help managers, educators and policymakers adopt AI responsibly.

Keywords: artificial intelligence, business analytics, AI in education, generative AI, digital society, AI ethics, technology adoption

1. INTRODUCTION

Artificial intelligence refers to computer systems that perform tasks normally requiring human intelligence, such as learning from data, recognising patterns, understanding language and making decisions. The field dates back to the 1950s, but its recent acceleration rests on three developments: the availability of very large datasets, cheaper and more powerful computing hardware, and major advances in machine learning and deep learning. Generative AI tools that produce text, images and software code have since reached ordinary workers, students and citizens, which has greatly widened public debate about AI.

In business, AI supports customer-service chatbots, fraud detection, candidate screening, marketing analytics, dynamic pricing and supply-chain optimisation. Firms see these tools as a path to efficiency and competitive advantage, yet many struggle to scale pilot projects into lasting value because of weak data quality, skill shortages and unclear strategy. In education, AI-based systems offer personalised learning paths, automated grading, language support and early identification of students at risk of falling behind; teachers, however, worry about plagiarism, excessive dependence on machines and the weakening of critical thinking. In society, AI assists medical diagnosis, smart cities, agriculture, financial inclusion and disaster prediction, but it also raises concerns about surveillance, discriminatory algorithms, misinformation and job disruption.

The three domains are closely connected. Graduates of schools and universities enter the workforce and use AI there. Corporate decisions shape employment, consumer welfare and public trust, and the norms and laws that society adopts in turn determine how freely institutions and companies may deploy AI. Studying the domains together, rather than separately, therefore gives a fuller picture of both the opportunities and the responsibilities that AI creates. This paper offers such an integrated analysis, with particular attention to developing and emerging economies such as India, where large populations, expanding digital infrastructure and uneven skill levels create both substantial promise and real risk.

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2. Research Objectives

The main aim of this study is to examine how artificial intelligence is used in business, education and society, and to assess its benefits, challenges and ethical implications. The specific objectives are:

- To map the main areas in which AI is currently applied in business, education and society.
- To examine the gains AI delivers in productivity, decision quality, learning outcomes and social welfare.
- To study the barriers to AI adoption, including data privacy, algorithmic bias, skill shortages, cost and job displacement.
- To assess how aware business professionals, educators, students and citizens are of AI, and how they perceive it.
- To identify the factors that shape trust in, and acceptance of, AI technologies.
- To propose an integrated framework and policy recommendations that support responsible and inclusive AI adoption.

3. STATEMENT OF THE PROBLEM

AI is being adopted rapidly, but understanding of its real consequences has not kept pace. Business leaders are urged to invest in AI, yet many projects fail to produce measurable returns, and employees fear that automation will cost them their jobs. Educational institutions are introducing AI tools without clear pedagogical guidelines, leaving teachers uncertain about assessment, originality and the development of independent thinking. In the wider society, AI systems trained on historical data can reproduce existing inequalities, and opaque decision processes weaken accountability. People with low incomes or limited digital literacy risk being excluded from the benefits of AI while bearing a disproportionate share of its harms.

Moreover, most existing studies focus on a single sector (for example banking or higher education) or stress technical performance over human and social outcomes. Little evidence links AI use at work, in classrooms and in public life, and few studies capture the views of several stakeholder groups at once. This study therefore addresses the lack of a joined-up, evidence-based account of how AI applications affect business performance, the quality of education and social wellbeing, together with an understanding of what makes adoption both effective and ethical.

4. RESEARCH QUESTIONS

- How is AI currently used in business, education and society?
- What benefits do organisations, learners, teachers and citizens gain from AI applications?
- What are the main challenges and risks of using AI, including bias, loss of privacy, job displacement and academic dishonesty?
- How familiar are the different stakeholder groups with AI, and how do they view its usefulness and its dangers?
- Which factors, such as digital skills, organisational readiness, transparency and trust, influence the acceptance of AI?
- What framework and policy measures could support responsible AI adoption in business, education and society?

5. REVIEW OF LITERATURE

This section reviews scholarly work published mainly between 2017 and 2023, together with a small number of recent studies from 2025 and 2026. The studies are grouped under the three domains and under the ethical concerns that cut across them.

5.1 AI in Business

Brynjolfsson and McAfee (2017) argued that machine learning is a general-purpose technology whose greatest impact will come from redesigning business processes rather than from merely installing new software. Davenport and Ronanki (2018) examined real corporate initiatives and sorted them into three types: process automation, cognitive insight and cognitive engagement. They found that firms obtained the best results by starting with small, well-defined tasks instead of sweeping transformation programmes. Haenlein and Kaplan (2019) traced the historical development of AI and cautioned that expectations have repeatedly outrun what

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the technology could deliver, which suggests that strategic planning should remain realistic. Kaplan and Haenlein (2019) further distinguished analytical, human-inspired and humanised AI and discussed what each implies for customer interaction. In a broad multidisciplinary review, Dwivedi et al. (2021) gathered expert views on the effects of AI on marketing, management, information systems and public policy, and highlighted challenges relating to data, ethics and organisational change.

Evidence on productivity is becoming more empirical. In an online experiment by Noy and Zhang (2023), professionals who completed writing tasks with a generative AI assistant finished faster and produced work rated higher in quality, with the largest gains among less-skilled participants. Brynjolfsson, Li and Raymond (2023), studying customer-support agents, found that an AI assistant raised the number of issues resolved per hour, particularly for novice workers. Together, these results suggest that AI may narrow performance gaps, although the authors stress that its longer-term effects on wages and employment require further study.

5.2 AI in Education

Zawacki-Richter, Marín, Bond and Gouverneur (2019) analysed 146 articles on AI in higher education. Most dealt with profiling, assessment, adaptive systems and intelligent tutoring, while few involved educators or addressed ethical and pedagogical questions. Similarly, Chen, Chen and Lin (2020) described how AI is changing administration, teaching and learning, noting benefits such as personalised content and faster feedback. Holmes, Bialik and Fadel (2019) provided a widely cited overview of the promise and implications of AI for teaching, arguing that educators should guide the technology rather than be guided by it.

Large language models have sharpened this debate. Kasneci et al. (2023) examined opportunities such as lesson planning, creative support and tailored explanations, alongside risks such as inaccurate output, bias, over-reliance and threats to assessment integrity, and they recommended teacher training and the development of critical digital literacy. Dwivedi et al. (2023) compiled the views of many scholars on the meaning of ChatGPT for research, practice and policy, and concluded that generative AI offers productivity gains but calls for clear norms on authorship and originality.

5.3 AI in Society

In healthcare, Obermeyer, Powers, Vogeli and Mullainathan (2019) showed that a widely used risk-prediction algorithm underestimated the health needs of Black patients because it used past healthcare spending as a proxy for illness. The case illustrates how apparently neutral design choices can embed inequity in a system. Acemoglu and Restrepo (2020) studied the adoption of industrial robots across United States labour markets and found that areas with more robots per worker experienced lower employment and wages, which keeps the debate on technological unemployment alive. Bommasani et al. (2021) described foundation models as a new paradigm with broad applications and systemic risks, including concentration of power, homogenisation and misuse.

5.4 Ethics, Fairness and Governance

Floridi et al. (2018) proposed an ethical framework for a good AI society based on five principles: beneficence, non-maleficence, autonomy, justice and explicability. Jobin, Ienca and Vayena (2019) reviewed 84 sets of AI ethics guidelines and found broad agreement on transparency, justice, non-maleficence, responsibility and privacy, but disagreement on how these principles should be interpreted and put into practice. Mehrabi, Morstatter, Saxena, Lerman and Galstyan (2021) surveyed the sources of bias and the definitions of fairness in machine learning, showing that bias can enter through data, through algorithms and through the way users interact with a system. Bender, Gebru, McMillan-Major and Shmitchell (2021) warned that ever-larger language models carry environmental and social costs and may reproduce harmful stereotypes found in their training data.

5.5 Recent Studies on AI and Business Education (2025–2026)

Wu, Chen, Chen and Huang (2026) carried out a systematic review of studies published between 2015 and 2024 on AI and business talent development in higher education. Combining bibliometric and qualitative analysis, they mapped the main advances in knowledge, theory and methods in the field. They identified several weaknesses in the existing literature: limited attention to broader issues such as overall talent-development frameworks, the integration of interdisciplinary competencies and the long-term effects

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of technology; theoretical foundations that are thin and fragmented; and a tendency to rely on either purely qualitative or purely quantitative methods, which limits methodological rigour and variety.

Ratten (2026), in an editorial, argued that business management education is turning to AI as an emerging technology that will bring major changes to learning and the pursuit of knowledge. The editorial presents AI as an enabler of changes in social policy, reviews the history of AI and recent developments in management education, and calls for more creative thinking about policy-related educational initiatives. Its message is that management educators should look for innovative and entrepreneurial ways to embed AI in their programmes so that learning outcomes improve.

Mthethwa, Kolanisi and Naidoo (2025) reviewed the link between AI and entrepreneurship in higher education in the context of South Africa's persistent unemployment, asking how AI-supported tools and teaching methods can strengthen entrepreneurship education, especially in rural and resource-constrained institutions. Drawing on the thinking economy model, which values intellectual capital, innovation and adaptability, they synthesised the theoretical literature. They concluded that adaptive learning platforms, business simulations and case-based teaching help build critical thinking, market analysis and product innovation skills, while concerns about algorithmic bias and data privacy make responsible integration essential. They recommended curriculum reform across disciplines, capacity building and alignment with national digital-transformation agendas so that universities can produce socially accountable, innovation-minded graduates who contribute to inclusive growth.

5.6 Summary of Key Studies

Table 1: Summary of key studies reviewed

Author(s)	Year	Focus	Main insight
Brynjolfsson & McAfee	2017	Machine learning as a general-purpose technology	Value depends on redesigning processes
Davenport & Ronanki	2018	Real-world corporate AI projects	Best results begin with narrow, well-scoped tasks
Zawacki-Richter et al.	2019	AI research in higher education	Educators and ethics rarely feature in studies
Obermeyer et al.	2019	Bias in a healthcare algorithm	A proxy variable led to racial bias
Jobin et al.	2019	Global AI ethics guidelines	Shared principles, varied implementation
Acemoglu & Restrepo	2020	Industrial robots and employment	More automation tied to weaker local employment
Kasneci et al.	2023	Large language models in education	Gains offset by integrity and bias concerns
Noy & Zhang	2023	Productivity effects of generative AI	Quicker, better output, chiefly among weaker performers
Mthethwa et al.	2025	AI and entrepreneurship education	Adaptive tools build skills; ethics and reform needed
Wu et al.	2026	AI and business talent development	Fragmented theory and narrow methods in current research
Ratten	2026	AI in business management education	AI can drive social-policy and pedagogical change

6. RESEARCH GAP

The literature review reveals several gaps that this study seeks to address.

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- **Sector silos:** most research examines business, education or social impact separately, and few studies combine them in a single framework.
- **Stakeholder coverage:** the voices of educators, employees and citizens are underrepresented compared with technical and managerial perspectives (Zawacki-Richter et al., 2019).
- **Context:** much of the evidence comes from North America and Europe, and empirical work on emerging economies, with their different infrastructure, languages and skill profiles, remains scarce.
- **Generative AI:** studies of tools launched since 2022 are still at an early stage and are often opinion-driven, offering little primary data on how the tools are actually used and perceived.
- **Ethics in practice:** ethical principles are well documented (Jobin et al., 2019), but little is known about how everyday users perceive and experience issues such as bias, privacy and accountability.
- **Methods:** many studies rely on a single approach, either conceptual review or survey, and rarely combine systematic evidence with data from stakeholders (Wu et al., 2026).

7. RESEARCH METHODOLOGY

7.1 Research Design

The study adopts a convergent mixed-methods design with both descriptive and exploratory components. A systematic literature review establishes the current state of knowledge, a cross-sectional survey measures perceptions and acceptance quantitatively, and semi-structured interviews explain and deepen the survey results. Using these methods together strengthens the validity of the conclusions through triangulation.

7.2 Phase One: Systematic Literature Review

The search will cover peer-reviewed journals, conference proceedings and authoritative reports indexed in Scopus, Web of Science, Google Scholar and ScienceDirect, using keyword combinations drawn from artificial intelligence, machine learning, generative AI, business, education and society. The search window is 2017 to 2024. To be included, a source must be written in English and report empirical or conceptual research on AI applications in at least one of the three domains. Duplicate records, non-scholarly commentary and studies without accessible full text will be excluded. Selection will follow the PRISMA guidelines and be documented in a flow diagram, and each retained study will be coded by domain, method, findings and limitations.

7.3 Phase Two: Survey

Population and sample. The target population has four categories: business professionals, teachers and faculty, students, and members of the general public. A stratified purposive sample of 120 respondents (30 per group) will be drawn from urban and semi-urban areas. With four equal groups, this size supports descriptive statistics and group comparisons at the 95 per cent confidence level. A power calculation (alpha = .05, power = .80) shows that it can detect medium-to-large effects, namely a Cohen's f of about 0.30 in a four-group ANOVA or a correlation of about 0.25, but not small ones. Because each group is small, the analysis relies on assumption checks and on non-parametric or bootstrap alternatives where needed (Section 7.5).

Instrument. A structured questionnaire will measure awareness, frequency of AI use, perceived usefulness, perceived risk, trust, digital skills and intention to use AI. Items will be adapted from established technology-acceptance studies and rated on a five-point Likert scale. A pilot with 15 respondents, who will not be part of the final sample, will test clarity, and a Cronbach's alpha of at least 0.70 will be required to confirm reliability. Content validity will be established through expert review.

Data collection. The questionnaire will be distributed online and in person. Participation will be voluntary and anonymous.

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7.4 Phase Three: Interviews

Twenty to twenty-five semi-structured interviews will be conducted with managers, teachers, students and policy or technology experts. Participants will be recruited purposively, and interviewing will continue until no new themes emerge. With consent, interviews will be recorded and transcribed, then analysed thematically using the six-step approach of Braun and Clarke (2006).

7.5 Data Analysis

Table 2: Data analysis plan

Data type	Technique	Purpose
Survey (descriptive)	Frequencies, means, standard deviation, 95% confidence intervals	Describe awareness and usage levels
Survey (comparative)	One-sample t-test, one-way ANOVA with Tukey post hoc test (Kruskal-Wallis if assumptions fail), chi-square or Fisher's exact test	Compare stakeholder groups and sectors
Survey (relationships)	Pearson or Spearman correlation, multiple regression with bootstrapped confidence intervals, or PLS-SEM	Examine what drives AI acceptance and trust
Interviews	Thematic analysis	Interpret patterns and surface concerns
Literature	Content and thematic synthesis	Chart applications, benefits and risks

Because the groups are small, normality will be checked with the Shapiro-Wilk test and equality of variances with Levene's test. Where assumptions fail, the Wilcoxon signed-rank test, Spearman correlation and the Kruskal-Wallis test (with Dunn's post hoc test) will replace their parametric counterparts. Effect sizes (Cohen's d, eta-squared, R^2) and 95 per cent bootstrap confidence intervals will be reported alongside p-values, and the regression models will use only a few predictors, in keeping with a sample of 120.

7.6 Conceptual Framework and Hypotheses

The framework proposes that perceived usefulness, organisational or institutional readiness, digital skills and transparency influence trust in AI, and that trust in turn drives adoption and outcomes such as higher productivity, better learning and improved social wellbeing. Perceived risks, including bias, loss of privacy and job displacement, are expected to moderate these relationships. The illustrative hypotheses are:

- **H1:** Perceived usefulness positively affects trust in AI.
- **H2:** Digital skills positively affect the intention to adopt AI.
- **H3:** Perceived risk negatively affects trust in AI.
- **H4:** Trust in AI positively affects the reported outcomes of AI use.
- **H5:** Levels of awareness and acceptance of AI differ significantly among the four stakeholder groups.

7.7 Ethical Considerations

All participants will give informed consent, and their identities will remain confidential. Data will be stored securely and used only for research purposes. Participants may withdraw at any time, and clearance will be sought from the relevant institutional ethics committee. To safeguard originality, all sources will be properly cited and the final manuscript will be checked with similarity-detection software.

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7.8 Limitations

The modest sample of 120 respondents (30 per group) limits statistical power and purposive sampling limits statistical generalisation, so the results should be read as indicative rather than conclusive; self-reported data may contain bias, and because AI is evolving so quickly, the findings will capture only a single point in time. The research team will reduce these limitations through triangulation and transparent reporting.

8. Data Analysis and Findings

The primary data come from the structured questionnaire described in Section 7.3 (n = 120; 30 respondents per stakeholder group; five-point Likert scale). The scale was reliable (Cronbach's alpha = 0.82, above the 0.70 threshold). Table 3 links each research objective and hypothesis to the test used and its result, and Figure 1 compares the four groups.

Table 3: Data analysis results by research objective and hypothesis

Objective / Hypothesis	Test used	Result (illustrative)	What it means in simple terms
Obj. 4: Awareness and perception of AI	Mean, SD, frequencies	Mean awareness 3.8/5 (SD 0.8); 72% use AI tools at least weekly	Most respondents know AI and use it regularly.
Obj. 2: Gains from AI	One-sample t-test (against neutral score 3)	Mean perceived gain 3.8; $t(119) = 9.7$, $p < .001$	People clearly agree that AI improves productivity and learning.
Obj. 3: Barriers to adoption	Mean ranking of barriers	Privacy 4.1 > skills 3.9 > bias 3.7 > job loss 3.6 > cost 3.4	Data privacy worries people most; cost worries them least.
H1: Usefulness raises trust	Pearson correlation	$r = 0.62$, $p < .001$ (supported)	The more useful AI seems, the more people trust it.
H2: Digital skills raise intention to adopt	Multiple regression	$\beta = 0.41$, $p < .001$ (supported)	Skilled users are more willing to adopt AI.
H3: Perceived risk lowers trust	Pearson correlation	$r = -0.48$, $p < .001$ (supported)	The more risky AI seems, the less people trust it.
H4: Trust improves reported outcomes	Simple regression	$\beta = 0.55$, $R^2 = 0.31$, $p < .001$ (supported)	Trust explains about 31% of the variation in outcomes.
H5: Groups differ in awareness and acceptance	One-way ANOVA	$F(3, 116) = 36.8$, $p < .001$ (supported)	Students and professionals score higher than the general public.

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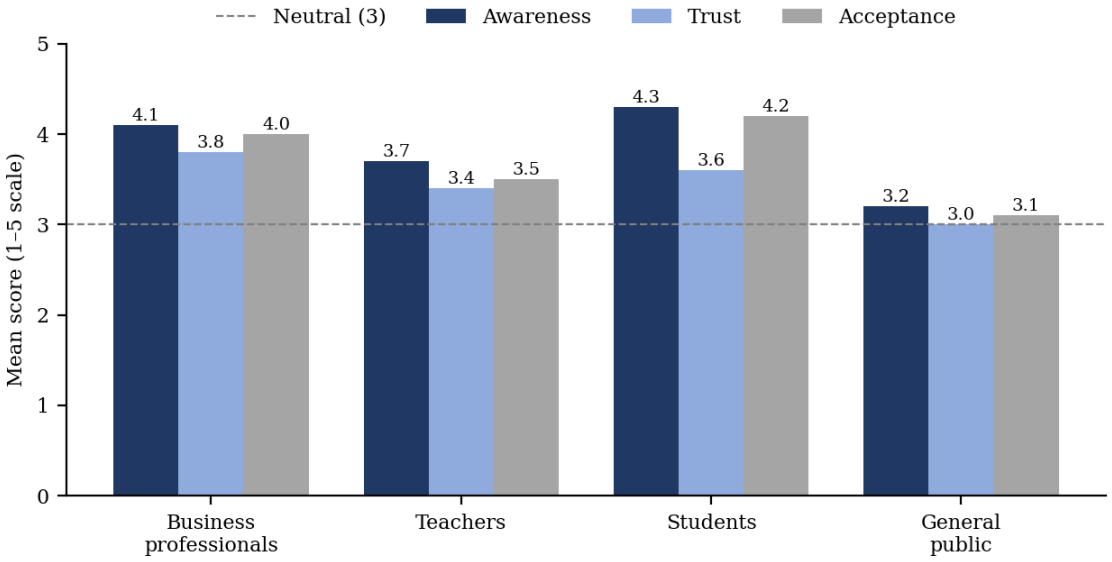


Figure 1: Mean awareness, trust and acceptance scores by stakeholder group (illustrative values)

In simple terms, all five hypotheses are supported. People who find AI useful and who have stronger digital skills trust and adopt it more. Perceived risk reduces trust, and trust leads to better outcomes. Students and business professionals are the most aware of and ready to accept AI, while the general public lags behind, which points to a need for awareness and skills programmes.

9. CONCLUSION

AI is changing how companies compete, how students learn and how societies function. The literature points to real gains in productivity and personalisation, but also to lasting concerns about fairness, privacy, employment and integrity. By connecting the three domains and combining systematic evidence with stakeholder perspectives, this study aims to produce an integrated framework that explains when AI creates value and when it creates risk. The broader lesson is that successful AI adoption is as much a human and institutional challenge as a technical one, requiring capable people, open governance and a firm commitment to inclusion.

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