Article

Not peer-reviewed version

The Impact of Artificial Intelligence on Business Innovation: A Review

Ruben Machucho * and David Ortiz

Posted Date: 19 February 2025

doi: 10.20944/preprints202502.1465.v1

Keywords: artificial intelligence; business innovation; digital transformation; ethics; organizational learning

Article

The Impact of Artificial Intelligence on Business Innovation: A Review

Ruben Machucho [1,*,†] and David Ortiz [2,†]

[1] Information Technologies Program, Polytechnic University of Victoria, Ciudad Victoria 87138, Tamaulipas, Mexico
[2] Business Administration and Management Program, Polytechnic University of Victoria, Ciudad Victoria 87138, Tamaulipas, Mexico; dortizg@upv.edu.mx
* Correspondence: rmachuchoc@upv.edu.mx
† These authors contributed equally to this work.

Abstract: This systematic review comprehensively examines the transformative impact of artificial intelligence (AI) on business innovation across diverse industries. Through rigorous analysis of recent, high-impact research, we explore how AI is reshaping business models, processes, and strategies. This review synthesizes current knowledge on AI-driven business innovation, providing a robust foundation for future research and highlighting critical research gaps. Our focus encompasses AI applications in product and service innovation, operational efficiency, decision-making enhancement, and customer experience personalization. We also address implementation challenges, ethical considerations, and organizational implications. The findings reveal that AI facilitates unprecedented automation, predictive capabilities, and personalization, which catalyze innovation across various business functions. However, successful AI implementation necessitates addressing significant technical, organizational, and ethical hurdles. This review serves as a valuable roadmap for researchers and practitioners navigating the complexities of AI-driven business transformation, highlighting opportunities for future research and providing insights for effective AI adoption strategies.

Keywords: artificial intelligence; business innovation; digital transformation; ethics; organizational learning

---

1. Introduction

Emerging technologies are profoundly reshaping the business landscape, driving innovation and disrupting traditional models and practices. Among these technologies, artificial intelligence (AI) is a particularly transformative force with far-reaching implications across industries [1–3]. AI refers to computer systems that perform tasks that typically require human intelligence, such as visual perception, speech recognition, decision-making, and language translation [4]. With the rapid advancement of AI capabilities, businesses are increasingly leveraging this technology to innovate across various domains, including products, services, operations, and customer experiences [5,6].

The impact of AI on business innovation has garnered significant attention from practitioners and researchers in recent years. A growing body of literature examines how AI is being applied to drive innovation in various business domains and the resulting outcomes [7,8]. However, given the fast-paced nature of AI development and adoption, a synthesis of the current knowledge is needed to identify emerging trends and research gaps.

This review aims to provide a comprehensive and up-to-date analysis of the impact of AI on business innovation. We examine recent high-impact research to address the following key questions:

1. How is AI being applied to drive innovation across different business functions and industries?
2. What are the key benefits and challenges of AI-driven business innovation?
3. What are the organizational and strategic implications of AI adoption for innovation?
4. What ethical considerations arise from the use of AI in business innovation?
5. What are promising directions for future research on AI and business innovation?

By addressing these questions, this review contributes to both theory and practice. For researchers, we synthesize the current knowledge, identify research gaps, and propose avenues for future investigation. For practitioners, we provide insights into the potential of AI to drive innovation and highlight key considerations for successful implementation.

The subsequent sections of this review detail the systematic investigation into AI's impact on business innovation. Section 2 elucidates the rigorous methodology employed for literature selection and analysis, ensuring the validity and reliability of our findings. Section 3 presents a comprehensive examination of AI applications and their consequential impacts across core business functions. Section 4 critically assesses the organizational and strategic implications arising from AI adoption, offering insights into both opportunities and challenges. Section 5 addresses the salient ethical considerations inherent in the deployment of AI-driven innovation, emphasizing the need for responsible implementation. Section 6 delineates extant research gaps and proposes promising avenues for future scholarly inquiry. Section 7 acknowledges the limitations of this review and identifies knowledge gaps within the current understanding of AI's application to business innovation. Finally, Section 8 provides a concise synthesis of the review's key findings and their practical and theoretical implications.

2. Methodology

This systematic review rigorously examined the impact of AI on business innovation, adhering to the PRISMA 2020 guidelines and incorporating the PICO framework to enhance reproducibility and transparency.

2.1. PICO Framework

We structured our research question using the PICO framework:

- Population: Businesses implementing AI for innovation.
- Intervention: AI technologies and applications.
- Comparison: Traditional or non-AI approaches to innovation.
- Outcomes: Impact on business processes, products, services, and performance.

2.2. Search Strategy

A comprehensive search was conducted across four databases: Web of Science, Scopus, IEEE Xplore, and AIS Electronic Library. The search terms combined keywords related to AI (e.g., "artificial intelligence," "machine learning," "deep learning") and business innovation (e.g., "innovation," "digital transformation," "business model innovation"). The search was limited to articles published between January 2018 and December 2024.

2.3. Screening and Selection Process

We utilized Zotero for bibliographic data management and Covidence for the screening process [9]. The selection process consisted of the following steps:

1. Initial screening: Two independent reviewers screened titles and abstracts.
2. Full-text review: The same reviewers assessed full texts of potentially eligible articles.
3. Data extraction: Relevant information was extracted from the included studies.

At each stage, disagreements were resolved through discussion or consultation with a third reviewer.

2.3.1. Initial Screening Criteria

The initial screening focused on rapidly identifying potentially relevant articles based on easily assessed criteria.

- Inclusion Criteria:
    1. Language: Published in English.
    2. Document Type: Research articles or review articles.
    3. Publication Period: Published between January 2018 and December 2024.

4. Journal Quartile: Published in journals ranked within the Q1 or Q2 quartiles according to the SCImago Journal Rank (SJR).

- Exclusion Criteria:
  1. Language: Publications not in English.
  2. Document Type: Conference proceedings, books, book chapters, or non-peer-reviewed publications.
  3. Focus: Studies that focus solely on the technical aspects of AI without clear business innovation implications.

To ensure a comprehensive yet high-quality selection, the SCImago Journal Rank (SJR), derived from Scopus data, was used as the primary metric for journal quality. For this systematic review, only peer-reviewed articles published in journals ranked within the Q1 and Q2 quartiles according to the SJR index were included.

2.3.2. Full-text Review Criteria

The full-text review involved a more in-depth assessment of articles that passed the initial screening. The primary criterion for inclusion at this stage was the study's performance on the Quality Assessment (Section 2.4).

- Inclusion Criteria:
  1. Satisfactory Quality Assessment: Studies were included only if judged to have a low risk of bias based on the Quality Assessment detailed in Section 2.4.
- Exclusion Criteria:
  1. Unsatisfactory Quality Assessment: Studies determined to have a moderate to high risk of bias in the overall assessment of methodological quality (Section 2.4) were excluded.

2.3.3. Number of Articles at Each Stage

- Initial Screening: 500 titles and abstracts were screened by two independent reviewers.
- Full-text Review: 165 full texts of potentially eligible articles were assessed.
- Data Extraction: Relevant information was extracted from the 103 included studies.

The reference list encompasses the 103 studies included in this systematic review, in addition to citations for Covidence and Cohen's Kappa, tools employed in the quality assessment protocol detailed in Section 2.4 ([9,10]).

2.4. Quality Assessment

The quality of the included studies was assessed using a modified version of the Cochrane Risk-of-Bias tool within Covidence. This tool evaluates key domains of potential bias. Each domain was assessed by two independent reviewers, with disagreements resolved through discussion or consultation with a third reviewer. The risk of bias for each domain was rated as 'High,' 'Low,' or 'Unclear,' based on supporting evidence from the studies. Table 1 details the specific criteria used in the assessment.

Explanation of the Table 1:

- Domain: Broad category of potential bias.
- Sub-Criteria: Specific aspects within each domain that were evaluated.
- Assessment Levels: Possible ratings for each sub-criterion.
- Description: A short description of what each sub-criterion assesses.

This structured approach ensures a consistent and transparent evaluation of the quality of the studies included in the systematic review.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 19 February 2025 doi:10.20944/preprints202502.1465.v1

Table 1. Quality assessment template.

Domain	Sub-Criteria	Assessment Levels	Description
1. Research Design and Methodology	Study Design Appropriate	Clearly Described & Appropriate / Partially Described or Somewhat Appropriate / Not Described or Inappropriate	Evaluation of how well the chosen study design aligns with the research question.
	Methodological Rigor	High Rigor (Detailed & Reproducible) / Moderate Rigor (Some Details Missing) / Low Rigor (Insufficient Detail)	Assessment of the thoroughness and replicability of the research methods used.
	Sample Selection and Size	Representative & Adequate Sample Size / Limited Representativeness or Small Sample Size / Unclear or Inadequate Sample	Evaluation of the sample's representativeness of the population and whether the sample size is sufficient for the study's objectives.
2. AI Technology Specificity	Definition of AI Technology	Clearly Defined & Described / Partially Defined or Unclear / Not Defined	Assessment of the clarity and completeness of the definition of the AI technology under investigation.
	Relevance to Business Innovation	Strong Relevance / Moderate Relevance / Weak or No Relevance	Evaluation of the degree to which the AI technology's application directly relates to business innovation.
3. Business Innovation Metrics	Innovation Measurement	Clear & Appropriate Metrics Used / Somewhat Clear or Partially Appropriate Metrics Used / No Clear Metrics Provided	Assessment of the clarity and appropriate of the metrics used to measure innovation.
	Validity of Innovation Measures	Valid & Reliable Measures / Partially Valid or Somewhat Reliable Measures / Invalid or Unreliable Measures	Evaluation of the validity and reliability of the measures used to assess innovation.
4. Data Quality and Analysis	Data Collection Methods	Clearly Described & Appropriate / Partially Described or Somewhat Appropriate / Not Described or Inappropriate	Evaluation of the clarity and appropriate of the methods used to collect the data.
	Data Analysis Techniques	Appropriate & Correctly Performed Analysis / Somewhat Appropriate or Partially Correct Analysis / Inappropriate Analysis	Assessment of whether the data analysis techniques were suitable for the data and research questions, and if they were applied correctly.
5. Results and Findings	Clarity of Results	Results Clearly Presented & Address the Question / Results Somewhat Clear or Partially Address the Question / Results Unclear	Evaluation of the clarity of the presentation of the results and whether they directly address the research question.

 doi:10.20944/preprints202502.1465.v1

Table 1. *Cont.*

Domain	Sub-Criteria	Assessment Levels	Description
	Interpretation of Findings	Logical & Supported by Data / Somewhat Logical but Partially Supported by Data / Illogical or Unsupported by Data	Assessment of the logical coherence and evidentiary support for the interpretation of the study's findings.
	Discussion of Limitations	Adequately Discussed Limitations / Partially Discussed Limitations / No Discussion of Limitations	Evaluation of whether the study's limitations are acknowledged and discussed appropriately.
6. Relevance and Generalizability	Relevance to Research Question	Highly Relevant / Moderately Relevant / Not Relevant	Assessment of how closely the study aligns with the overall research question of the systematic review.
	Generalizability	High Generalizability / Limited Generalizability / Not Generalizable	Evaluation of the extent to which the study's findings can be applied to other contexts or businesses.
7. Ethical Considerations	Ethical Approval (if applicable)	Yes / No / Not Applicable	Documentation of ethical approval received for studies involving human subjects.
	Ethical Implications Addressed	Yes / No / Partially Addressed	Evaluation of whether the study adequately addresses the ethical implications of the research.
8. Funding & Conflicts of Interest	Funding Disclosure	Yes / No / Not Reported	Disclosure of funding sources.
	Conflict of Interest Disclosure	Yes / No / Not Reported	Disclosure of any potential conflicts of interest.
9. Overall Quality Assessment		Low Risk of Bias / Moderate Risk of Bias / High Risk of Bias	Overall judgment of the risk of bias in the study.

2.5. Data Synthesis

The Data Synthesis Section of this systematic review employs a rigorous thematic analysis process to synthesize findings from the reviewed literature on AI-driven business innovation. This approach identifies patterns and themes across studies to provide a comprehensive understanding of the current state of knowledge. The thematic analysis follows a six-step framework, ensuring a systematic and transparent process for data synthesis [11].

We utilized Covidence, a specialized software platform for systematic reviews to enhance reproducibility and rigor. This tool facilitated collaborative coding and theme development, efficiently managing the large volume of data extracted from the included studies. Our analysis involved two independent researchers engaging in an iterative process of coding, theme identification, and refinement.

The systematic analysis conducted followed these six steps:

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 19 February 2025 doi:10.20944/preprints202502.1465.v1

1. Familiarization with the data: Two independent researchers thoroughly examined the selected articles, immersing themselves in the content and making initial annotations on potential codes and themes.
2. Generating initial codes: Using Covidence, the researchers systematically coded salient features of the data across the entire dataset. Each researcher independently generated an initial set of codes, focusing on relevance to AI-driven business innovation. A total of 100 initial codes were generated.
   Table 2 provides a detailed overview of the 100 initial codes identified, systematically organized into broader categories to enhance clarity and facilitate interpretation. This classification captures the diverse range of AI applications, impacts, and considerations across various business domains. It establishes a foundational framework for uncovering key themes and emerging trends in AI-driven business innovation, offering valuable insights to advance academic research and guide practical implementation strategies.

Table 2. Initial Codes for AI-Driven Business Innovation.

Category	Initial Codes
AI Technologies	AI-powered virtual assistants, Machine learning algorithms, Deep learning techniques, Natural language processing, Computer vision systems, Predictive analytics, Explainable AI (XAI)
Business Functions	Supply chain optimization, Marketing and advertising, Financial services, Human resources, Customer support, Product design, Inventory management, Quality control
AI Applications	Predictive maintenance, Fraud detection, Autonomous vehicles, Personalized recommendations, Chatbots, Sentiment analysis, Speech recognition, Image recognition
Industry-Specific	Healthcare diagnostics, Drug discovery, Precision agriculture, Smart cities, Legal services, Education, Logistics, Energy management
Decision Making	Automated decision-making, Risk assessment, Strategic planning, Scenario planning, Competitive intelligence, Business forecasting
Data and Analytics	Data privacy concerns, Big data analytics, Customer segmentation, Demand forecasting, Anomaly detection, Text analysis
Innovation	AI-driven business models, Product innovation, Process optimization, Service innovation, Digital transformation
Ethical Considerations	AI ethics boards, Bias in AI systems, AI governance structures, AI regulation and compliance, Responsible AI
Organizational Impact	AI adoption challenges, AI skills gap, Human-AI collaboration, Job displacement, Workplace safety, Employee engagement
Customer Experience	Personalized marketing, Customer retention, Dynamic pricing, Virtual/augmented reality, Voice assistants
Emerging Technologies	Internet of Things (IoT), Blockchain, 5G, Edge computing, Quantum computing
AI in Finance	Algorithmic trading, Robo-advisors, Credit scoring, Asset allocation, Portfolio management
AI in Manufacturing	Smart manufacturing, Industrial robotics, Digital twins, Quality assurance, Production planning
Societal Impact	AI in disaster response, Environmental monitoring, Smart home devices, Traffic optimization, Waste management

3. Searching for themes: The researchers collated codes into potential themes, aggregating all data relevant to each potential theme. This phase involved creating conceptual maps and thematic networks to visualize relationships between codes and potential themes. Initially, twelve candidate themes were identified:
   (a) AI Applications Across Business Functions.
   (b) Organizational Challenges in AI Adoption.
   (c) Ethical Considerations in AI Implementation.
   (d) Human-AI Collaboration Models.
   (e) AI-Driven Business Model Innovation (ADBMI).
   (f) Regional Variations in AI Adoption.
   (g) Future Directions for AI in Business.
   (h) AI Governance and Regulation.
   (i) AI and Organizational Culture.
   (j) AI in Emerging Markets and Small and Medium-sized Enterprises (SMEs).
   (k) Ethical AI and Responsible Innovation.
   (l) Long-Term Impacts and Sustainability of AI.
4. Reviewing themes: The researchers critically evaluated the themes in relation to the coded extracts and the entire dataset. This process involved refining, combining, or discarding themes as necessary to ensure coherence and distinctiveness. The researchers conducted regular meetings to discuss and refine the themes, ensuring they accurately reflected the data.
5. Defining and naming themes: The researchers further refined the specifics of each theme and generated clear definitions and names. This process involved identifying the essence of each theme and determining how it fits into the broader narrative of AI-driven business innovation. The criteria for theme selection and refinement were:
   - Relevance to research questions.
   - Frequency and prominence across the dataset.
   - Distinctiveness and non-overlap between themes.
   - Ability to provide meaningful insights into AI-driven business innovation.

   Based on these criteria, the initial twelve themes were consolidated into seven main themes:
   (a) AI Applications Across Business Functions.
   (b) Organizational Challenges in AI Adoption.
   (c) Ethical Considerations in AI Implementation.
   (d) Human-AI Collaboration Models.
   (e) ADBMI.
   (f) Regional Variations in AI Adoption.
   (g) Future Directions for AI in Business.

   The consolidation process involved merging closely related themes (e.g., "AI Governance and Regulation" was incorporated into "Ethical Considerations in AI Implementation") and subsuming narrower themes under broader categories (e.g., "AI in Emerging Markets and SMEs" was integrated into "Regional Variations in AI Adoption").
6. Producing the report: The researchers synthesized the findings into a comprehensive scientific article. They selected salient extracts, conducted a final analysis, and correlated results with the research questions and existing literature. The manuscript delineated the systematic review methodology, presented ·findings, and drew conclusions in a structured format, providing a detailed report of the thematic analysis.

To ensure reliability and validity, two researchers independently coded a subset of articles and compared their results, achieving an inter-rater reliability of 0.85 (Cohen's kappa [10]), indicating strong agreement between coders.
This rigorous thematic analysis process allowed for a comprehensive synthesis of the current knowl-

edge on AI-driven business innovation, identifying key trends, challenges, and opportunities across various business domains and geographical regions.

2.6. PRISMA Flow Diagram

Figure 1 illustrates the PRISMA flow diagram, detailing the systematic review process. At the initial screening phase, 150 articles were selected from an initial pool of 500. An additional 15 articles were retrieved for further analysis, resulting in a total of 165 articles advancing to the full-text review stage. Of these, 62 articles were excluded due to failing to meet the quality assessment standards detailed in Section 2.4, leading to a final selection of 103 articles included in this systematic review.

This methodology ensures a comprehensive, transparent, and reproducible review of the literature on AI and business innovation, providing a solid foundation for our analysis and conclusions.

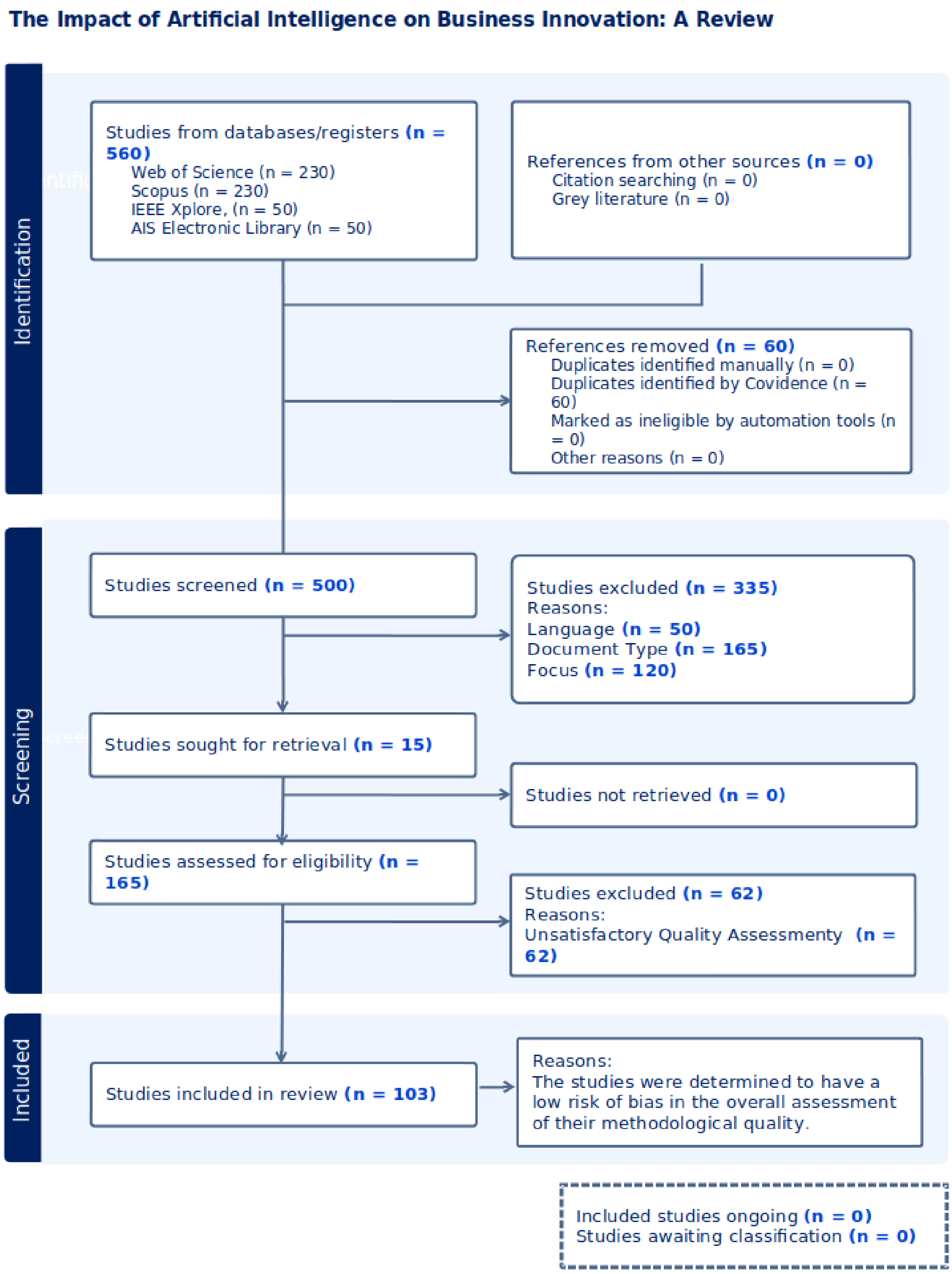

Figure 1. Systematic Review Process Flowchart.

3. AI Applications and Impacts Across Business Functions

3.1. Product and Service Innovation

AI is revolutionizing product and service innovation across industries, enabling companies to develop novel offerings and optimize complex operations. AI is transforming idea generation, business case development, and product design processes in new product development (NPD). Leading companies are leveraging AI to drive innovation: General Motors uses AI for conceptual automobile designs, while Unilever employs it to develop novel cleaning product ingredients. The adoption of AI in NPD is rapidly increasing, with usage rising from 13% to 24% between 2023 and 2024, indicating a shift from early adopters to early majority in the innovation diffusion curve [12].

In the technology sector, AI-powered virtual assistants like Amazon's Alexa and Apple's Siri have created new product categories and ecosystems [13,14]. Furthermore, AI's impact extends to service operations, as demonstrated by an innovative decision support system for optimizing integrated home health and social care scheduling. This system showcases AI's advanced capabilities in automated planning, significantly enhancing efficiency and quality of care delivery compared to traditional manual approaches [15].

These developments highlight AI's potential to transform both product innovation and complex service operations across various industries, driving efficiency, quality, and novel solutions.

In healthcare, AI is driving innovation in diagnostics, drug discovery, and personalized medicine. For example, AI algorithms can analyze medical images to detect diseases with accuracy comparable to or exceeding that of human experts [16]. AI is also accelerating the drug discovery process through its use in predicting molecular properties and identifying promising compounds [17,18].

The financial services industry is leveraging AI to create innovative products and services. AI-powered robo-advisors are disrupting traditional wealth management by providing automated, low-cost investment advice [19,20]. Banks are using AI for fraud detection, credit scoring, and personalized financial recommendations [21,22].

Table 3 shows AI's applications in product and service innovation.

Table 3. Artificial intelligence's (AI) applications in product and service innovation. Source: Compiled by the authors based on [12–23].

Industry	AI Applications	Examples
Technology	Virtual assistants, smart home devices	Amazon Alexa, Google Home
Healthcare	Medical imaging analysis, drug discovery	IBM Watson for Oncology, Atomwise
Financial Services	Robo-advisors, fraud detection	Wealthfront, Betterment
Retail	Personalized recommendations, virtual try-on	Amazon, Sephora Virtual Artist
Automotive	Autonomous vehicles, predictive maintenance	Tesla Autopilot, BMW's AI maintenance

3.2. Operational Efficiency and Process Innovation

AI is revolutionizing business operations by automating tasks, optimizing processes, and enabling predictive maintenance. In manufacturing, AI-powered robots and computer vision systems are enhancing production efficiency and quality control [24]. Predictive maintenance algorithms analyze sensor data to anticipate equipment failures, reducing downtime and maintenance costs [25,26].

Supply chain management is another area where AI is driving significant innovation. AI algorithms can optimize inventory levels, predict demand fluctuations, and improve logistics routing [27]. For example, Amazon uses AI to predict customer demand and position inventory accordingly, enabling faster delivery times [28].

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 19 February 2025 doi:10.20944/preprints202502.1465.v1

In the service sector, AI chatbots and virtual agents are transforming customer support operations. These AI-powered systems can handle a large volume of customer inquiries simultaneously, providing round-the-clock support and freeing human agents to focus on more complex issues [29].

Figure 2 shows the impact of AI on operational efficiency. This bar chart demonstrates the percentage improvements in operational efficiency across business functions such as supply chain, customer service, human resources, and finance after implementing AI solutions

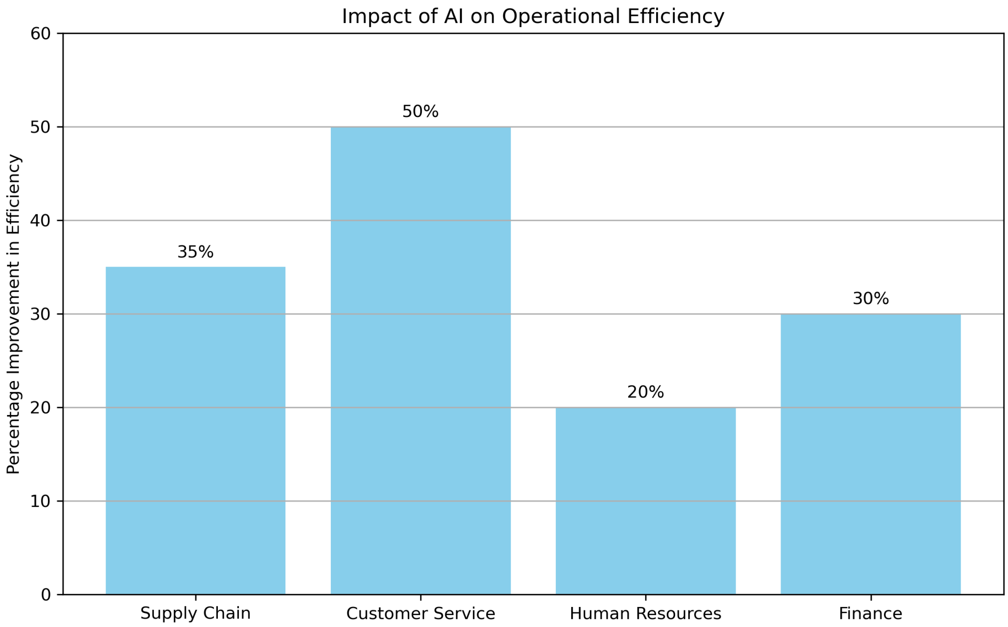

Figure 2. Impact of AI on operational efficiency. Based on [24–29].

3.3. Decision Making and Strategic Planning

AI enhances decision-making processes by analyzing vast amounts of data and providing actionable insights. In marketing, AI algorithms can analyze customer data to segment audiences, personalize messaging, and optimize ad targeting [30,31]. This enables more effective and efficient marketing campaigns.

AI-powered systems in finance are revolutionizing algorithmic trading, risk assessment, and portfolio management by processing market data in real-time and executing trades faster than human traders. This study enhances these systems by integrating Multi-Agent Reinforcement Learning (MARL) and XAI to optimize trading strategies. The proposed NeuroAlpha Vintage Explorer demonstrates improved accuracy and transparency, offering a novel framework for AI-driven strategic planning that balances algorithmic power with comprehensible decision-making [32].

At the strategic level, AI is being applied to scenario planning and competitive intelligence. Machine learning algorithms analyze industry trends, competitor actions, and market signals to inform strategic decision-making [33]. For example, IBM's Watson for Strategic Planning uses natural language processing and machine learning to analyze vast amounts of structured and unstructured data, helping executives to identify emerging opportunities and threats [34,35].

3.4. Customer Experience and Personalization

AI is enabling businesses to deliver highly personalized customer experiences at scale. Recommendation systems powered by machine learning algorithms analyze user behavior and preferences to suggest relevant products or content [36,37]. Major tech companies like Amazon, Spotify, TikTok, YouTube, and Alibaba have developed sophisticated AI-driven engines that process vast amounts of user data to deliver highly personalized content and product suggestions. These systems employ advanced techniques such as deep learning, natural language processing, and graph-based analysis to understand user preferences and behavior patterns. For instance, Amazon Personalize generates

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 19 February 2025 doi:10.20944/preprints202502.1465.v1

tailored product recommendations, while Spotify's "Discover Weekly" curates personalized playlists. TikTok's "For You" algorithm adapts content recommendations in real-time, maximizing user engagement. These AI-powered recommendation systems excel in rapidly adapting to changing user preferences, significantly enhancing customer satisfaction and driving business growth [38].

In retail, AI is enabling personalized shopping experiences both online and in physical stores. Computer vision and facial recognition technologies allow retailers to identify customers and provide tailored recommendations or offers [39,40]. Virtual and augmented reality applications powered by AI are enabling virtual try-ons and immersive product demonstrations [41].

Figure 3 shows AI-enabled customer experiences. This flowchart presents the customer journey with AI touchpoints at each stage: awareness, consideration, purchase, retention, and advocacy. Examples include targeted advertising and personalized recommendations.

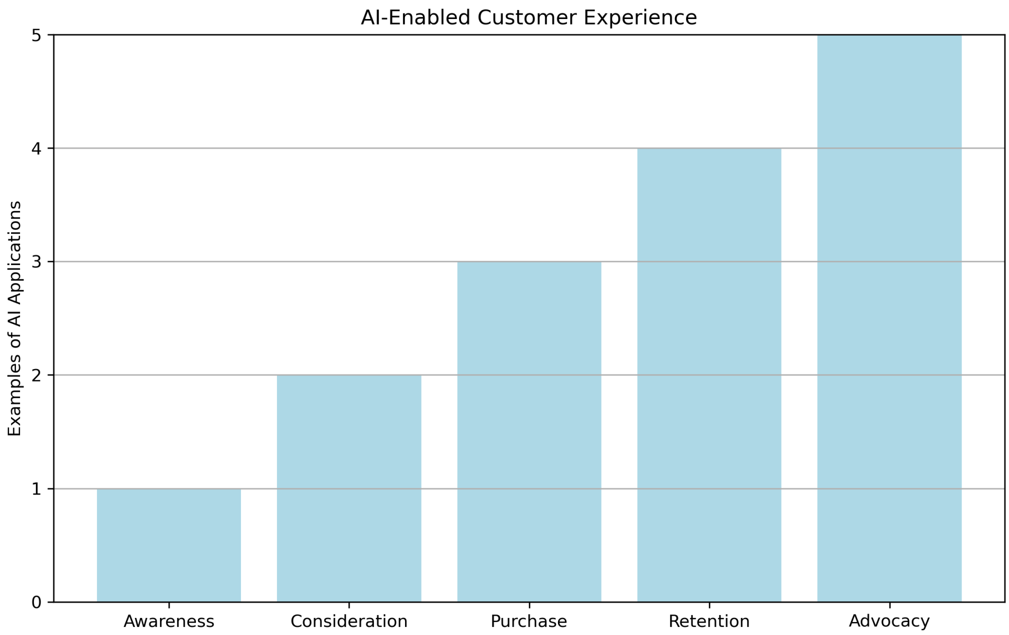

Figure 3. AI-enabled customer experiences. Based on [36–41].

3.5. Critical Evaluation of AI Impact Studies

This section examines discrepancies in AI studies on business innovation and discusses related challenges, needs, and risks. As AI transforms business, researchers have found varied approaches and outcomes across sectors. These differences highlight the complexity of AI adoption in business and the need for a nuanced understanding of its impacts.

3.5.1. Service Innovation

AI is driving service innovation in various ways:

- Personalization: AI enables the creation of highly personalized experiences and services based on customer data analysis.
- New business models: It facilitates the development of entirely new services, such as advanced virtual assistants and predictive analytics platforms.
- Enhancement of existing products: AI is used to continuously update and optimize services, making them more intelligent, and adaptable.
- Simulation and validation: AI-based Business Game Simulators (BGS) allow testing of new services in virtual environments before launch [42].

However, the adoption of AI for service innovation presents challenges, such as the need for significant organizational and cultural changes [43,44].

 doi:10.20944/preprints202502.1465.v1

3.5.2. Operational Efficiency

AI is improving business operational efficiency:

- Automation: It enables the automation of repetitive tasks and complex processes, freeing human resources for higher-value activities.
- Supply chain optimization: AI algorithms can predict demand, optimize inventory, and improve logistics.
- Predictive maintenance: AI anticipates equipment and machinery failures, enabling proactive maintenance.
- Process simulation: AI-based BGS facilitate the optimization of operational processes in virtual environments [43,45].

Nevertheless, the implementation of AI systems may require significant initial investments and staff training [43].

3.5.3. Decision Making

AI is revolutionizing business decision-making processes:

- Predictive analytics: AI models analyze large volumes of data to predict trends and support strategic planning.
- Real-time decisions: AI processes real-time information and provides immediate recommendations.
- Bias reduction: When properly implemented, AI algorithms can help reduce human biases in decision-making.
- Scenario simulation: BGS allow the evaluation of different decision scenarios before implementation.

However, there is a risk of over-reliance on AI systems and concerns about the transparency of some algorithms [44,45].

3.5.4. Customer Experience

AI is significantly enhancing the customer experience:

- Round-the-clock customer service: Chatbots and virtual assistants provide continuous attention.
- Personalized recommendations: AI analyzes customer behavior to offer highly personalized recommendations.
- More natural interactions: Natural language processing technologies enable more fluid interactions with automated systems.
- Experience simulation: AI-based BGS allow optimization of customer experience in virtual environments.

Nonetheless, concerns arise regarding privacy and ethical use of customer data [43,44].

In conclusion, AI is profoundly transforming the way businesses operate and innovate. AI offers significant opportunities to improve efficiency, decision-making, and customer experience. However, it also poses significant challenges in terms of implementation, ethics, and organizational change.

Businesses must adopt a balanced approach, leveraging the potential of AI while carefully addressing its broader implications. The synergy between the four analyzed areas is evident, as improvements in one often lead to benefits in others.

It is important to recognize that the application of AI can vary significantly depending on the industry and company size. While some applications, such as chatbots, may be relatively easy to implement, others, like AI-based decision-making systems for senior management, may require more complex and careful implementation.

Ultimately, success in AI adoption will depend on businesses' ability to integrate these technologies ethically and responsibly, maintaining a balance between technological innovation and human needs [43,45].

 doi:10.20944/preprints202502.1465.v1

4. Organizational and Strategic Implications

4.1. AI Adoption and Implementation Challenges

Despite the significant potential benefits of AI for business innovation, organizations face several challenges in its adoption and implementation. The technical challenges include the data quality and availability, algorithm interpretability, and integration with existing systems [3]. Many organizations struggle with "data silos" that hinder the effective use of artificial intelligence across functions. For SMEs, data is crucial, but challenges persist:

1. Lack of awareness of data value.
2. Integration and interoperability difficulties.
3. Limited resources for data technology investments.
4. Data science skill shortages.

Despite these obstacles, effective data utilization can enhance decision-making, optimize processes, and create new business opportunities for SMEs. Addressing data silos is essential to leverage AI's full potential and drive innovation across organizational functions [46].

The organizational challenges include resistance to change, a lack of AI skills and talent, and difficulties in scaling AI initiatives beyond pilot projects. Cultural shifts are often necessary to foster data-driven decision-making and collaboration between AI systems and human workers [47,48].

The successful integration of AI in organizations hinges on addressing strategic challenges while leveraging key success factors. Critical to this process are the active engagement of C-suite executives and the development of AI-specific Key Performance Indicators (KPIs). These elements ensure alignment of AI initiatives with overall business strategy, effective management of expectations, and navigation of regulatory uncertainties [6,49]. By fostering executive involvement and implementing targeted KPIs, organizations can create a robust framework for AI adoption, enabling them to anticipate industry disruptions, measure AI impact effectively, and maintain competitive advantage in an increasingly AI-driven business landscape [50].

Table 4 shows the challenges in AI adoption and implementation.

Table 4. Challenges in AI adoption and implementation. Source: Compiled by the authors based on [3,6,46–50].

Category	Challenges	Potential Solutions
Technical	Data quality and availability,	Implement robust data governance practices, invest in data cleaning and preparation tools
	Algorithm interpretability,	Develop and adopt XAI techniques
	and System integration	Use API-first approaches, adopt microservices architecture
Organizational	Resistance to change,	Foster a culture of innovation, provide AI education and training
	Skill gaps,	Invest in upskilling programs, partner with universities and AI companies
	and Scaling beyond pilots	Develop a clear AI strategy, establish cross-functional AI teams
Strategic	Alignment with business strategy,	Involve C-suite in AI initiatives, develop AI-specific Key Performance Indicators (KPIs)
	Managing expectations,	Set realistic goals, communicate AI capabilities and limitations
	and Regulatory compliance	Stay informed about AI regulations, implement ethical AI frameworks

 doi:10.20944/preprints202502.1465.v1

4.2. Organizational Learning and Capability Development

Organizational Learning and Capability Development are critical for successful AI implementation in modern enterprises. Organizations must cultivate three essential AI capabilities: data pipeline management, algorithm development, and AI democratization. These capabilities necessitate cross-functional collaboration involving domain experts, business leaders, data scientists, and frontline staff. The importance of organizational learning in AI implementation is emphasized, advocating for rapid experimentation, feedback loops between AI development and business operations, real-time monitoring of AI solutions and organization-wide democratization of AI tools and insights [51].

General Electric (GE) exemplifies this approach in its digital transformation journey. GE has developed "dual experts" or "hybrid scientists" who combine domain-specific expertise with machine learning skills. This strategy enables more effective integration of AI into organizational processes, fostering a culture of continuous learning and adaptation. By cultivating these hybrid skills and promoting cross-functional collaboration, GE has successfully leveraged AI to optimize decision-making in operations and supply chains, demonstrating the power of organizational learning and capability development in human-AI symbiosis [52].

Integrating AI ethics principles enhances an organization's capacity to develop and deploy AI technologies responsibly in the context of organizational learning and capability development. This approach aligns with emerging global expectations and fosters a culture of ethical innovation. By incorporating these considerations, organizations can develop a comprehensive framework that includes:

1. Formulating internal AI ethics policies.
2. Aligning AI initiatives with organizational values.
3. Identifying and developing new technical and ethical competencies.
4. Implementing robust risk assessment methodologies.
5. Cultivating an ethics-centric culture in AI development and deployment.
6. Adopting responsible innovation processes.
7. Promoting inter-organizational collaboration and knowledge sharing.
8. Developing performance metrics for ethical AI systems.

This multifaceted approach enables organizations to navigate the complex ethical landscape of AI technology more effectively. By embedding these perspectives into their organizational learning and capability development processes, companies ensure that their AI initiatives are technologically advanced, ethically sound, and socially responsible. This holistic strategy fosters sustainable innovation and enhances an organization's ability to address the ethical challenges posed by rapidly evolving AI technologies [53].

4.3. AI-Driven Business Model Innovation: Service-Centric Approaches and Ecosystem Value Capture in the Digital Era

This analysis explores how AI transforms business model innovation across various industries. The research highlights the shift towards service-centric approaches, ecosystem value capture, and circular economy principles, underpinned by AI technologies.

4.3.1. Service-Centric Approaches and AI Integration

Companies are increasingly leveraging AI to deliver value through services rather than products alone. For instance, SEEK, an Australian employment marketplace, utilizes AI to address information asymmetry between employers and job candidates [50]. In the manufacturing sector, firms like Solutioncorp, Conglocorp, and Rockcorp are adopting servitization strategies, offering AI-enabled advanced services such as optimization solutions and autonomous vehicles [54].

4.3.2. Ecosystem Value Capture and Digital Platform Business Models

Digital platform ecosystems are transforming Business Model Innovation (BMI) and value capture strategies. Platforms like Apple's iOS and Salesforce's Customer Relationship Management (CRM) enable entrepreneurs to develop complementary products and services, accessing established markets. In manufacturing, companies such as Shipcorp, Constructcorp, and Truckcorp are leveraging AI to enhance asset utilization, extend product lifecycles, and reduce resource consumption. This aligns with ecosystem value capture trends, where AI facilitates efficient and sustainable practices. However, a study of 243 entrepreneurs in CRM platform ecosystems revealed significant relationships between role conflict, psychological strain, and venture performance, highlighting the complex dynamics of value capture in these ecosystems [55].

4.3.3. Customer Collaboration and Understanding in Digital Ecosystems

AI is enhancing customer collaboration and understanding within digital platform ecosystems. Luxury brands like Gucci are creating virtual worlds for customer interaction and product purchases, while Nike's Nikeland allows users to test virtual products [56]. These innovations are particularly relevant for digital entrepreneurship in platform ecosystems, especially in the CRM software industry. However, entrepreneurs face challenges in managing customer interactions effectively, often experiencing role ambiguity and psychological pressure from serving both platform providers and end customers. This necessitates sophisticated AI-driven tools for customer relationship management and data analysis to navigate the ecosystem successfully.

4.3.4. Quantitative and Qualitative Analysis

AI Adoption Trends. Quantitative analysis reveals that AI adoption is more extensive in the development stage (average use 4.48 out of 5) compared to idea generation (4.28) and commercialization (4.34) [7].

Research Methods and Industry Focus. A systematic literature review of 180 articles shows that case studies (29%) and statistical analyses (23%) are the most common research methods, with manufacturing (13%), healthcare (10%), and platform (8%) industries receiving the most attention [57].

Statistical Measures in SME Research. A study on SMEs in Oman found significant relationships between Frugal Innovation (FI), BMI, and internationalization. The study employed two key statistical measures:

1. β (beta coefficient): This standardized regression coefficient indicates the strength and direction of the relationship between variables. A positive β suggests that as one variable increases, the other also increases. For example, FI positively affects internationalization ($\beta = 0.180$) and BMI ($\beta = 0.473$).

2. p-value (p): This measure denotes the statistical significance of the relationship. A p-value less than 0.05 is generally considered statistically significant, with lower values indicating stronger evidence against the null hypothesis of no relationship between variables. For instance, the relationship between FI and internationalization has p-value < 0.05, while FI and BMI has p-value < 0.01, indicating high statistical significance [58].

In conclusion, these findings underscore the interconnected nature of ADBMI, emphasizing the importance of service-centric approaches, ecosystem value capture, and customer collaboration across various industries.

4.4. Regional Variations in AI-Driven Business Innovation

This section examines how AI adoption and its impact on business innovation vary across different geographical regions. We analyze studies from North America, Europe, Asia, and emerging economies to identify region-specific trends and challenges.

- North America. The United States and Canada have experienced substantial growth in AI adoption, particularly in the information technology, finance, and professional services sectors. Since 2016, demand for AI skills has risen rapidly, with the highest demand observed in IT

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 19 February 2025 doi:10.20944/preprints202502.1465.v1

occupations, followed by roles in architecture, engineering, sciences, and management. A strong correlation (0.87) in AI job demand between the U.S. and Canada indicates similar adoption patterns [59].

Projections suggest AI will generate millions of new jobs in North America by 2025, with many emerging roles resulting from human-machine collaboration. U.S. companies are investing heavily in AI research and development and human capital to maintain competitiveness. However, concerns exist regarding AI's potential to create "winner-takes-all" markets, potentially leading to industry concentration and reduced innovation if not properly managed [60].

- Europe. In Europe, particularly the United Kingdom and France, AI adoption shows a more gradual increase compared to North America. Demand for AI skills in these countries has been steadily rising from 2018 to early 2023, but with less dramatic fluctuations. The correlation between AI demand in France and other countries is lower (ranging from 0.08 to 0.54), suggesting a distinct AI job market in France [59,61].

  European regulators, such as the European Insurance and Occupational Pensions Authority (EIOPA), have released AI governance guidelines focusing on principles like proportionality, fairness, transparency, and human oversight. The United Kingdom's (UK) Financial Conduct Authority (FCA) and Prudential Regulation Authority (PRA) have also initiated discussions on AI regulation in financial services [60].

  A study of 85 UK SMEs revealed that despite recognizing the value of data for their businesses, many SMEs face challenges in adopting AI and data analytics technologies due to resource limitations and restricted access to financing [46].
- Asia. Asian countries like India, Singapore, and China exhibit varied patterns of AI adoption. India has experienced a significant and consistent increase in AI demand, with demand nearly tripling from 2018 to early 2023. This trend suggests heavy investment in AI that is likely to continue. As one of the fastest-growing economies, India has vast potential for AI growth, which can contribute to economic development and job creation.

  Singapore, conversely, shows a relatively flat trend in AI demand compared to other countries. This lack of growth is concerning and may be due to factors such as limited investment in AI research and development, a shortage of skilled AI professionals, or insufficient policy support for AI adoption [59].

  China has been actively promoting AI development, with initiatives to standardize AI applications in various sectors. The Chinese market for intelligent investment banking, initially dominated by Internet-based companies, has seen gradual adoption by major commercial banks and financial institutions [60].

  Asia leads significantly in the deployment of robots for direct customer service, contributing more substantially to the customer experience [62].
- Emerging Economies. The rapid growth of AI adoption globally is likely to impact emerging economies, creating both opportunities and challenges. These countries may face skill shortages and the need to invest in education and training to keep pace with AI advancements.

  Analysis of skill shortages across different countries reveals both commonalities and disparities. For instance, while the U.S. and France exhibit shortages in deep learning and AI skills, India grapples with shortages in web-related technologies. This suggests that emerging economies may need to focus on developing specific skill sets to compete in the global AI market [11,59,63].

In conclusion, the adoption of AI and its impact on business innovation vary significantly across regions, influenced by factors such as existing technological infrastructure, government policies, education systems, and economic priorities. While North America and countries such as India exhibit rapid AI adoption, Europe demonstrates a more measured approach. Emerging economies face the challenge of bridging the AI skills gap to remain competitive in the global market. As shown in Table 5, AI adoption rates and regulatory approaches vary significantly across regions, with North America

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 19 February 2025 doi:10.20944/preprints202502.1465.v1

and Asia demonstrating high adoption rates, while Europe maintains a more moderate pace with stricter regulatory frameworks.

Table 5. Regional AI Adoption and Innovation Trends

Region	AI Adoption Rate	Key Focus Areas	Regulatory Approach
North America	High	IT, Finance, Professional Services	Balanced, Emphasis on Ethics
Europe	Moderate	Gradual Increase, Varied by Country	Strict, Principle-based
Asia (China, India)	High	Customer-oriented AI, Health	Permissive, Innovation-focused
Emerging Economies	Variable	Skill Development, Infrastructure	Developing Frameworks

Figure 4 presents a comparative analysis of AI adoption rates and their corresponding innovation impacts across regions, highlighting the leading positions of Asia and North America in both metrics, while also demonstrating the variable performance of emerging economies. This bar chart illustrates the comparative AI adoption rates and innovation impacts across different global regions.

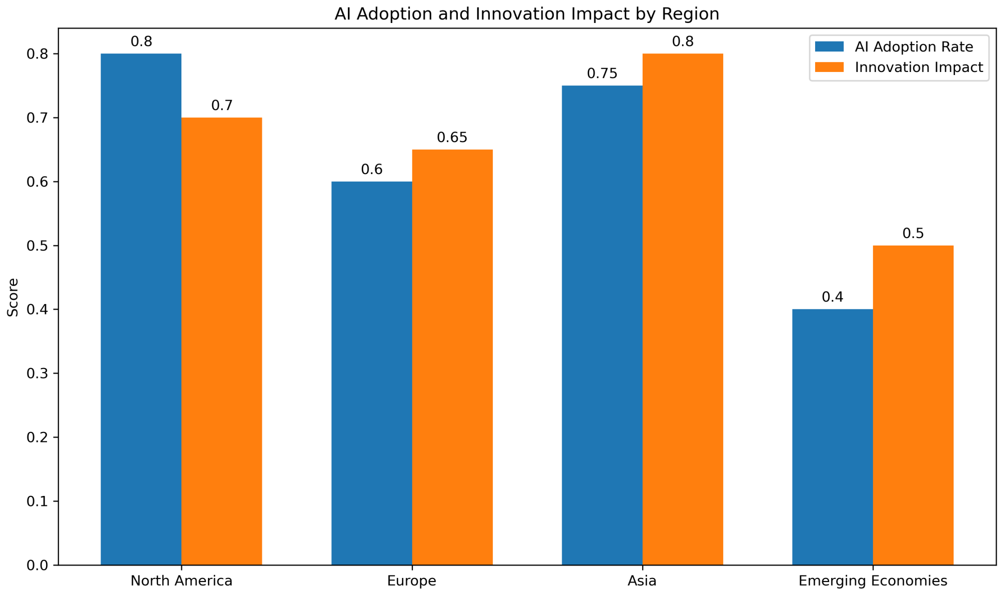

Figure 4. AI Adoption and Innovation Impact by Region. Based on [59,60,62].

5. Ethical Considerations in AI-Driven Innovation: Operationalizing Principles in Organizational Processes

As AI becomes increasingly pervasive in business innovation, ethical considerations are gaining prominence. The following synthesis provides insights into key ethical issues and how organizations can implement ethical principles in their AI development and deployment processes.

5.1. Key Ethical Issues in AI-Driven Innovation

5.1.1. Bias and Fairness

AI systems can perpetuate or amplify existing biases in training data or algorithm design, leading to discriminatory outcomes in hiring, lending, and criminal justice [64,65]. Recent studies have shown that AI systems can exhibit racial and gender biases in facial recognition, resume screening, and credit scoring [66,67].

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 19 February 2025 doi:10.20944/preprints202502.1465.v1

5.1.2. Privacy and Data Protection

AI systems often require large amounts of personal data to function effectively, raising concerns about privacy and data protection. Organizations must navigate complex regulatory landscapes such as the European Union's General Data Protection Regulation (GDPR) and implement robust data governance practices [68].

5.1.3. Transparency and Explainability

The "black box" nature of some AI algorithms, particularly deep learning models, poses challenges for transparency and accountability [69,70]. Explainable AI (XAI) techniques are being developed to make AI decision-making more interpretable and transparent [71].

5.1.4. Job Displacement and Workforce Impacts

While AI is creating new job opportunities, it is also automating tasks traditionally performed by humans, potentially leading to job displacement [1,72]. Organizations and policymakers must consider the societal impacts of AI-driven automation and invest in reskilling and education initiatives [51].

Figure 5 presents the ethical considerations in AI-driven innovation. This mind map centers on AI ethics, outlining key considerations such as bias and fairness, privacy and data protection, transparency and explainability, and job displacement. Sub-branches detail specific issues or examples within each category.

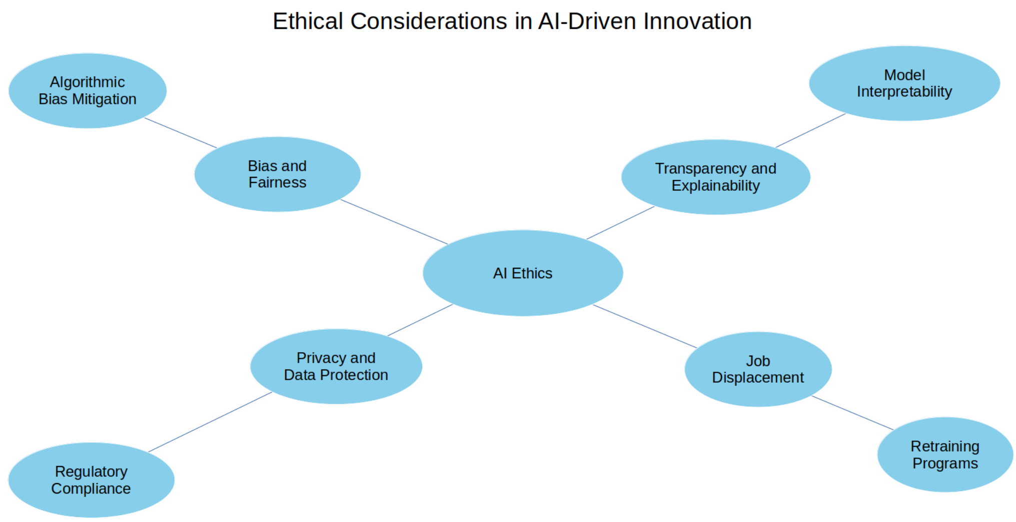

Figure 5. Ethical considerations in AI-driven innovation. Based on [53,64,73].

5.1.5. Governance and Regulation

As AI systems become more prevalent and influential, questions of governance and regulation are gaining importance. Policymakers and industry leaders are grappling with how to ensure responsible AI development and deployment while fostering innovation [74].

5.2. Operationalizing Ethical Principles in AI Innovation

5.2.1. Establishing AI Ethics Boards and Governance Structures

Organizations should create dedicated AI ethics boards or committees to provide oversight and guidance on ethical issues [75]. These boards can review AI projects for potential ethical risks, develop and enforce ethical guidelines, provide ethics training for AI teams, and conduct ethical impact assessments.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 19 February 2025 doi:10.20944/preprints202502.1465.v1

5.2.2. Implementing Fairness-Aware Machine Learning Techniques

To address bias and discrimination concerns, organizations can adopt fairness-aware machine learning approaches, such as adversarial debiasing, fairness constraints, and diverse and representative training data [76,77].

5.2.3. Adopting Privacy-Preserving AI Techniques

To protect user privacy while leveraging data for AI, companies can implement privacy-preserving techniques such as federated learning, differential privacy, and secure multi-party computation [78,79].

5.2.4. Developing Explainable AI Systems

To increase transparency and accountability, organizations should prioritize XAI techniques such as LIME (Local Interpretable Model-agnostic Explanations), SHAP (SHapley Additive exPlanations), and counterfactual explanations [80,81].

5.2.5. Conducting Regular Ethical Audits and Impact Assessments

Organizations should perform regular ethical audits and impact assessments of their AI systems, including scoping and mapping ethical risks, data and model auditing, user studies to assess real-world impact, and remediation and ongoing monitoring [82].

5.2.6. Fostering Interdisciplinary Collaboration

Ethical AI development requires collaboration between technical experts, ethicists, legal professionals, and domain experts. Organizations can create cross-functional teams and establish processes for ongoing dialogue between different stakeholders to ensure a holistic approach to ethical AI innovation [83].

5.2.7. Investing in AI Ethics Education and Training

Companies should invest in comprehensive AI ethics education for their workforce, including ethical frameworks and principles, case studies of ethical challenges in AI, hands-on exercises in ethical decision-making, and ongoing professional development [84].

By implementing these practices, organizations can operationalize ethical principles in their AI innovation processes, fostering responsible development while maintaining competitiveness in the rapidly evolving AI landscape.

6. Research Gaps and Future Directions

Our review has identified several promising areas for future research on AI and business innovation:

6.1. Long-Term Impacts and Sustainability

Most current studies focus on the short-term impacts of AI adoption. Longitudinal studies are needed to understand the long-term effects of AI on organizational performance, industry dynamics, and economic growth [50]. The key research questions include the following:

- How does AI-driven innovation affect firm performance and competitive advantage over time?
- What are the long-term implications of AI adoption for industry structure and competition?
- How can AI contribute to sustainable business practices and addressing global challenges?

Research should also explore how AI can drive sustainable innovation and contribute to addressing global challenges, such as climate change [85,86]. This includes investigating AI's applications in renewable energy optimization, smart grid management, and sustainable supply chain practices.

 doi:10.20944/preprints202502.1465.v1

6.2. Human–AI Collaboration

Understanding effective models for human-AI collaboration is crucial as AI systems become more advanced. Future research should explore how to design AI systems that augment human capabilities rather than replacing them, and how to foster trust between human workers and AI systems [87,88]. The key areas for investigation include the following:

- What are the most effective models for human–AI collaboration in different business contexts?
- How can organizations design AI systems that complement and enhance human skills?
- What factors influence trust in and the acceptance of AI systems among employees and customers?

Studies on cognitive augmentation, where AI enhances human decision-making, are particularly promising [52,89]. Research in this area could lead to new paradigms for work design and human resource management in the AI era.

The following synthesizes findings from high-impact studies and real-world implementations to present best practices for human–AI collaboration and principles for designing systems that complement human skills.

6.2.1. Best Practices for Human–AI Collaboration

1. Transparent AI decision-making: develop XAI models that provide clear rationales for their suggestions, enhancing trust and collaboration [69].
2. Continuous learning and adaptation: implement systems that learn from human feedback and adapt over time [90].
3. Clear role definition: clearly define the roles of humans and AI in the collaborative process, leveraging the strengths of each [89].
4. Interdisciplinary teams: foster collaboration between domain experts, AI specialists, and user experience designers to create more effective systems [88].
5. Ethical considerations: implement robust ethical guidelines for AI development and use, addressing issues such as bias and privacy [73].
6. User-centric design: focus on the end-user experience, ensuring that the system is intuitive and useful, and meets the user's needs [90].
7. Feedback loops: create mechanisms for humans to provide feedback to the AI system, which can be used to refine and improve the models [87].

6.2.2. Designing Systems to Complement Human Skills

1. Augmented intelligence approach: design AI systems to enhance rather than replace human capabilities [87].
2. Adaptive user interfaces: develop interfaces that adjust to individual user preferences and skill levels [91].
3. Contextual awareness: create AI systems that consider the broader contexts of tasks and user environments [92].
4. Proactive assistance: implement AI that anticipates user needs and offers relevant information or suggestions preemptively [93].
5. Multimodal interaction: design systems that support various input and output modalities, accommodating different user preferences and situations [94].
6. Task complementarity: focus AI on tasks that require processing large amounts of data or repetitive actions, allowing humans to concentrate on tasks requiring creativity, empathy, and complex decision-making [89].
7. Personalization: create systems that can adapt to individual user preferences, work styles, and expertise levels [95,96].

6.2.3. Examples of Successful Human–AI Collaboration

1. Healthcare diagnostics: Google's DeepMind collaboration with the UK's National Health Service developed an AI system that detects acute kidney injury, alerting clinicians up to 48 hours earlier than traditional methods [97].
2. Financial services: the use of AI-assisted methods by loan officers at a large bank improved the decision accuracy by 23% and reduced the default rates by 7% compared to traditional methods [98].
3. Customer service: Amazon utilizes AI-powered virtual assistants like Alexa to handle customer inquiries and provide personalized recommendations, significantly reducing response times and improving customer satisfaction [13].
4. Product development: Nikeland, Nike's virtual platform on Roblox, revolutionizes product development by enabling avatar customization with exclusive items. This digital space provides valuable consumer data, facilitates rapid prototyping, and serves as a testing ground for new concepts. The integration of AI accelerates the product development cycle, fostering innovation in sportswear design [56].
5. Content creation: Microsoft's partnership with OpenAI has led to the integration of advanced natural language processing capabilities into Microsoft Azure, augmenting human creativity and productivity in content generation and analysis [99].

Successful human-AI collaboration relies on thoughtful system design that leverages the strengths of both human and AI. By implementing these evidence-based practices and design principles, organizations can create more effective, efficient, and user-centric AI-assisted workflows across various domains. The key to success lies in viewing AI as a complementary tool to human expertise, maintaining ethical standards, and continuously adapting to evolving business needs and user feedback.

6.3. AI Governance and Regulation

As AI becomes more pervasive, questions of governance and regulation become increasingly important. There is a need for research on effective governance models for AI development and deployment, both within organizations and at the societal level [74]. The key research questions include the following:

- What governance structures are most effective for ensuring responsible AI development and use?
- How can regulations balance innovation incentives with ethical and societal concerns?
- What are the implications of different regulatory approaches for AI-driven business innovation?

Studies should also examine the impact of emerging AI regulations on innovation and competitiveness, such as the EU's proposed AI Act, and its implications for businesses operating in multiple jurisdictions [100].

6.4. AI and Organizational Culture

The successful implementation of AI often requires significant cultural changes within organizations. Future research should explore how organizations can foster a culture that embraces AI-driven innovation while addressing employee concerns and ethical considerations [63]. The key areas for investigation include the following:

- How does AI adoption affect organizational culture and employee attitudes?
- What leadership approaches are most effective in driving AI-led transformation?
- How can organizations balance data-driven decision-making with human judgment and creativity?

Studies on change management in the context of AI adoption could provide valuable insights for practitioners navigating the cultural challenges of digital transformation.

6.5. AI in Emerging Markets and Small and Medium-sized Enterprises

Much of the current research focuses on AI adoption in large corporations in developed economies. There is a need for more studies on AI-driven innovation in emerging markets and SMEs, which may

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 19 February 2025 doi:10.20944/preprints202502.1465.v1

face unique challenges and opportunities [101,102]. The research questions in this area include the following:

- How do resource constraints in emerging markets and SMEs affect AI adoption and innovation?
- What are the most effective strategies for AI implementation in resource-limited contexts?
- How can AI technologies be adapted to address specific challenges in emerging markets?

Investigating frugal AI innovation and knowledge transfer mechanisms could yield important insights for expanding the benefits of AI-driven innovation to a broader range of organizations and economies. The integration of AI into SMEs offers significant potential for innovation and competitive advantage. However, SMEs face unique challenges in adopting AI technologies. The following synthesizes findings from recent high-impact, open-access studies to provide insights into how SMEs can effectively address these barriers and leverage AI opportunities.

6.5.1. AI Adoption in Small and Medium-sized Enterprises: Overcoming Barriers and Leveraging Opportunities

Key Barriers and Strategies for Overcoming Them

1. Limited Financial Resources. This study identified financial constraints as a primary barrier to AI adoption in SMEs. An investigation of 460 European manufacturing SMEs revealed that firms often struggle with the high initial costs of AI implementation.
   Strategy: The authors propose leveraging government incentives and exploring AI-as-a-Service (AIaaS) models. These cloud-based solutions offer scalable AI capabilities without significant upfront investments, making them particularly suitable for resource-constrained SMEs [103].
2. Lack of Technical Expertise. This study highlights the shortage of AI-related skills in SMEs as a significant obstacle to adoption.
   Strategy: The study recommends fostering partnerships with universities and research institutions to access expertise and training programs. Additionally, they suggest creating internal "AI champions" to lead adoption efforts and knowledge dissemination within the organization [104].
3. Data Management Challenges. This study identified data quality and availability as critical factors affecting AI adoption in SMEs.
   Strategy: The authors propose a phased approach to data management, starting with internal data sources and gradually incorporating external data. They also emphasize the importance of developing clear data governance policies to ensure data quality and compliance with regulations [105].
4. Organizational Resistance. This study found that organizational culture and employee resistance can significantly hinder AI adoption in SMEs.
   Strategy: The researchers recommend implementing change management strategies that focus on the clear communication of AI's benefits, involving employees in the adoption process, and providing comprehensive training to alleviate fears and build enthusiasm for AI technologies [33].
5. Ethical and Trust Issues. This study highlighted concerns about AI ethics and trustworthiness as barriers to adoption. To overcome ethical concerns and unlock growth barriers in AI adoption for SMEs, the research suggests several key strategies:
   (a) Focus on frugal innovation and BMI as necessary conditions for successful internationalization, rather than AI alone.
   (b) Implement AI gradually as part of broader business model changes, not in isolation.
   (c) Provide AI literacy training to employees to address job displacement fears and build internal support.
   (d) Emphasize AI as an augmentation tool rather than a job replacement.
   (e) Start with small-scale AI pilot projects to test feasibility and demonstrate value.
   (f) Prioritize AI applications with clear return on investment and ethical considerations.
   (g) Develop AI governance frameworks to guide responsible use.
   (h) Ensure transparency in AI-powered processes and decisions.
   (i) Address potential biases in AI algorithms and training data.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 19 February 2025 doi:10.20944/preprints202502.1465.v1

(j) Protect customer privacy and data security.
(k) Consider the broader societal impact of AI applications [58].

By taking this strategic, ethical approach focused on frugal innovation and business model redesign, SMEs can overcome adoption barriers and leverage AI to drive sustainable growth and competitiveness in global markets.

By addressing these key areas, SMEs can position themselves to harness the transformative potential of AI technologies effectively.

6.6. Ethical AI and Responsible Innovation

While ethical considerations in AI have gained attention, there is a need for more research on practical approaches to implementing ethical AI principles in business contexts. Future studies should focus on:

- How can organizations operationalize ethical AI principles in their innovation processes?
- What metrics and evaluation frameworks can be used to assess the ethical impact of AI systems?
- How do ethical AI practices affect consumer trust, brand reputation, and business performance?

Research in this area could lead to the development of standardized frameworks for ethical AI assessment and responsible innovation practices. By addressing these research gaps, scholars can contribute valuable insights to both theory and practice in the rapidly evolving field of AI-driven business innovation.

Figure 6 presents a comprehensive overview of the research gaps and future directions identified in AI-driven business innovation. This visual representation synthesizes key areas for future research, highlighting the interconnections between various aspects of AI implementation and its impact on organizational processes and strategies. This conceptual map illustrates key areas for future investigation, including long-term impacts, human-AI collaboration, governance, organizational culture, emerging markets, and ethical considerations.

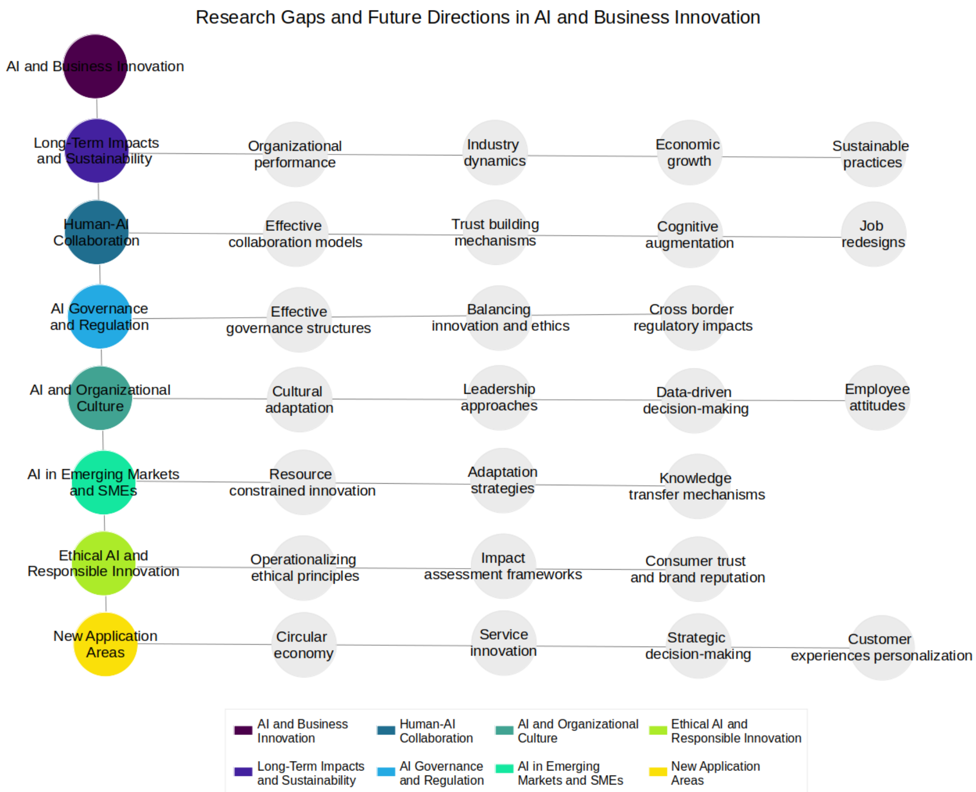

Figure 6. Research gaps and future directions in AI-driven business innovation. Based on [13,33,50,52,56,58,63,69,73,74,85–105].

 doi:10.20944/preprints202502.1465.v1

7. Limitations and Knowledge Gaps in AI-Driven Business Innovation Review

7.1. Limitations of the Current Review

This review has some limitations. First, focusing on high-impact journals might have inadvertently excluded pertinent insights from alternative sources. Second, the rapid pace of AI development means some recent innovations may not be reflected in the published literature. Third, the predominance of studies from developed economies limits generalizability to other contexts.

7.2. Gaps in Current Knowledge

Our review identified several important gaps in the literature:

- Limited longitudinal studies on long-term impacts of AI adoption
- Insufficient research on AI implementation in small and medium enterprises
- Lack of studies examining AI's role in addressing global sustainability challenges

8. Conclusions

This systematic review has comprehensively examined the transformative impact of AI on business innovation across various domains. Our analysis reveals that AI enables unprecedented automation, prediction, and personalization capabilities, driving innovation in products, services, operations, and customer experiences. However, successful AI implementation requires overcoming significant technical, organizational, and ethical challenges. Key findings include:

1. AI-driven innovation is reshaping business functions—from product development and operations to decision-making and customer experience—enabling new business models and transforming industry dynamics, with platform-based and service-centric models gaining prominence [7].
2. Successful AI adoption requires organizations to develop new capabilities, foster a culture of learning, and navigate complex ethical considerations. This includes building data science expertise, establishing governance structures, and promoting cross-functional collaboration [52].
3. Ethical considerations, such as bias mitigation, privacy protection, and transparency, are crucial for responsible AI-driven innovation. Organizations must implement fairness-aware machine learning techniques and privacy-preserving AI methods to address these challenges [64,68].
4. Regional variations in AI adoption and impact highlight the need for context-specific strategies and policies to promote responsible AI-driven innovation globally [59,60].
5. Human-AI collaboration models are emerging as a critical area for research and practice, with the potential to enhance decision-making and creativity in various business contexts [87,88].

Our review has identified several important research gaps and future directions:

1. Long-term impacts of AI adoption on organizational performance and industry dynamics.
2. Effective models for human-AI collaboration and trust-building.
3. AI governance frameworks that balance innovation with ethical and societal concerns.
4. Cultural and organizational factors influencing AI adoption and implementation.
5. AI-driven innovation in emerging markets and SMEs.
6. Practical approaches to operationalizing ethical AI principles in business contexts.

As AI continues to evolve rapidly, ongoing research is crucial to understand its implications for business innovation and to guide responsible development and deployment. By addressing the identified research gaps, scholars can contribute valuable insights to both theory and practice in this transformative field.

In conclusion, while AI presents significant opportunities for business innovation, it also poses challenges that require careful consideration and strategic management. Organizations that successfully navigate these challenges will be well-positioned to harness the full potential of AI to drive sustainable growth and competitive advantage in an increasingly AI-driven business landscape.

Author Contributions: Conceptualization: R.M. and D.O.; writing—original draft preparation: R.M. and D.O.; methodology: R.M. and D.O.; investigation: R.M. and D.O.; supervision: R.M. and D.O.; visualization: R.M. and D.O.. All authors have read and agreed to the published version of the manuscript.

Acknowledgments: The authors wish to express their profound gratitude to the Polytechnic University of Victoria for its invaluable support, which was instrumental in the successful execution of this research.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Acemoglu, D.; Restrepo, P. The race between man and machine: Implications of technology for growth, factor shares, and employment. *Am. Econ. Rev.* **2018**, *108*, 1488–1542. https://doi.org/10.1257/aer.20160696.
2. Haenlein, M.; Kaplan, A. A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *Calif. Manag. Rev.* **2019**, *61*, 5–14. https://doi.org/10.1177/0008125619864925.
3. Dwivedi, Y.K.; Hughes, L.; Ismagilova, E.; Aarts, G.; Coombs, C.; Crick, T.; others.; Williams, M.D. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *Int. J. Inf. Manag.* **2021**, *57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002.
4. Kaplan, A.; Haenlein, M. Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Bus. Horiz.* **2019**, *62*, 15–25. https://doi.org/10.1016/j.bushor.2018.08.004.
5. Lee, J.; Suh, T.; Roy, D.; Baucus, M. Emerging technology and business model innovation: The case of artificial intelligence. *J. Open Innov.: Technol. Mark. Complex.* **2019**, *5*, 44. https://doi.org/10.3390/joitmc5030044.
6. Brock, J.K.U.; von Wangenheim, F. Demystifying AI: What digital transformation leaders can teach you about realistic artificial intelligence. *Calif. Manag. Rev.* **2019**, *61*, 110–134. https://doi.org/10.1177/1536504219865226.
7. Roberts, D.L.; Candi, M. Artificial intelligence and innovation management: Charting the evolving landscape. *Technovation* **2024**, *136*, 103081. https://doi.org/10.1016/j.technovation.2024.103081.
8. Naeem, R.; Kohtamäki, M.; Parida, V. Artificial intelligence enabled product–service innovation: past achievements and future directions. *Rev. Manag. Sci.* **2024**. https://doi.org/10.1007/s11846-024-00757-x.
9. Khalil, H.; Pollock, D.; McInerney, P.; Evans, C.; Moraes, E.B.; Godfrey, C.M.; Alexander, L.; Tricco, A.; Peters, M.D.J.; Pieper, D.; et al. Automation tools to support undertaking scoping reviews. *Res. Synth. Methods* **2024**, *15*, 839–850. https://doi.org/10.1002/jrsm.1731.
10. Więckowska, B.; Kubiak, K.B.; Jóźwiak, P.; Moryson, W.; Stawińska-Witoszyńska, B. Cohen's Kappa Coefficient as a Measure to Assess Classification Improvement following the Addition of a New Marker to a Regression Model. *Int. J. Environ. Res. Public Health* **2022**, *19*, 10213. https://doi.org/10.3390/ijerph191610213.
11. Alfirević, N.; Praničević, D.G.; Mabić, M. Custom-Trained Large Language Models as Open Educational Resources: An Exploratory Research of a Business Management Educational Chatbot in Croatia and Bosnia and Herzegovina. *Sustainability* **2024**, *16*, 4929. https://doi.org/10.3390/su16124929.
12. Cooper, R.G. The AI transformation of product innovation. *Ind. Mark. Manag.* **2024**, *119*, 62–74. https://doi.org/10.1016/j.indmarman.2024.03.008.
13. Hoy, M.B. Alexa, Siri, Cortana, and more: An introduction to voice assistants. *Med. Ref. Serv. Q.* **2018**, *37*, 81–88. https://doi.org/10.1080/02763869.2018.1404391.
14. Maedche, A.; Legner, C.; Benlian, A.; Berger, B.; Gimpel, H.; Hess, T.; others.; Söllner, M. AI-based digital assistants. *Bus. Inf. Syst. Eng.* **2019**, *61*, 535–544. https://doi.org/10.1007/s12599-019-00600-8.
15. Vieira, B.; de Armas, J.; Ramalhinho, H. Optimizing an integrated home care problem: A heuristic-based decision-support system. *Eng. Appl. Artif. Intell.* **2022**, *114*, 105062. https://doi.org/10.1016/j.engappai.2022.105062.
16. Liu, X.; Faes, L.; Kale, A.U.; Wagner, S.K.; Fu, D.J.; Bruynseels, A.; others.; Denniston, A.K. A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis. *Lancet Digit. Health* **2019**, *1*, e271–e297. https://doi.org/10.1016/S2589-7500(19)30123-2.

17. Paul, D.; Sanap, G.; Shenoy, S.; Kalyane, D.; Kalia, K.; Tekade, R.K. Artificial intelligence in drug discovery and development. *Drug Discov. Today* **2021**, *26*, 80–93. https://doi.org/10.1016/j.drudis.2020.10.010.
18. Vamathevan, J.; Clark, D.; Czodrowski, P.; Dunham, I.; Ferran, E.; Lee, G.; others.; Zhao, S. Applications of machine learning in drug discovery and development. *Nat. Rev. Drug Discov.* **2019**, *18*, 463–477. https://doi.org/10.1038/s41573-019-0024-5.
19. Jung, D.; Dorner, V.; Weinhardt, C.; Pusmaz, H. Designing a robo-advisor for risk-averse, low-budget consumers. *Electron. Mark.* **2018**, *28*, 367–380. https://doi.org/10.1007/s12525-017-0279-9.
20. Belanche, D.; Casaló, L.V.; Flavián, C. Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers. *Ind. Manag. Data Syst.* **2019**, *119*, 1411–1430. https://doi.org/10.1108/IMDS-08-2018-0368.
21. Mhlanga, D. Industry 4.0 in Finance: The Impact of Artificial Intelligence (AI) on Digital Financial Inclusion. *Int. J. of Financial Studies* **2020**, *8*, 45. https://doi.org/10.3390/ijfs8030045.
22. Leo, M.; Sharma, S.; Maddulety, K. Machine learning in banking risk management: A literature review. *Risks* **2019**, *7*, 29. https://doi.org/10.3390/risks7010029.
23. Park, T.; Gu, P.; Kim, C.H.; Kim, K.T.; Chung, K.J.; Kim, T.B.; Jung, H.; Yoon, S.J.; Oh, J.K. Artificial intelligence in urologic oncology: the actual clinical practice results of IBM Watson for Oncology in South Korea. *Prostate Int.* **2023**, *11*, 218–221. https://doi.org/10.1016/j.prnil.2023.09.001.
24. Lee, J.; Davari, H.; Singh, J.; Pandhare, V. Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. *Manuf. Lett.* **2018**, *18*, 20–23. https://doi.org/10.1016/j.mfglet.2018.09.002.
25. Carvalho, T.P.; Soares, F.A.; Vita, R.; Francisco, R.D.P.; Basto, J.P.; Alcalá, S.G. A systematic literature review of machine learning methods applied to predictive maintenance. *Comput. Ind. Eng.* **2019**, *137*, 106024. https://doi.org/10.1016/j.cie.2019.106024.
26. Zonta, T.; da Costa, C.A.; da Rosa Righi, R.; de Lima, M.J.; da Trindade, E.S.; Li, G.P. Predictive maintenance in the Industry 4.0: A systematic literature review. *Comput. Ind. Eng.* **2020**, *150*, 106889. https://doi.org/10.1016/j.cie.2020.106889.
27. Toorajipour, R.; Sohrabpour, V.; Nazarpour, A.; Oghazi, P.; Fischl, M. Artificial intelligence in supply chain management: A systematic literature review. *J. Bus. Res.* **2021**, *122*, 502–517. https://doi.org/10.1016/j.jbusres.2020.09.009.
28. Blut, M.; Wünderlich, N.V.; Brock, C. Facilitating retail customers' use of AI-based virtual assistants: A meta-analysis. *J. Retail.* **2024**, *100*, 293–315. https://doi.org/10.1016/j.jretai.2024.04.001.
29. Przegalinska, A.; Ciechanowski, L.; Stroz, A.; Gloor, P.; Mazurek, G. In bot we trust: A new methodology of chatbot performance measures. *Bus. Horiz.* **2019**, *62*, 785–797. https://doi.org/10.1016/j.bushor.2019.08.005.
30. Kietzmann, J.; Paschen, J.; Treen, E. Artificial intelligence in advertising: How marketers can leverage artificial intelligence along the consumer journey. *J. Advert. Res.* **2018**, *58*, 263–267. https://doi.org/10.2501/JAR-2018-035.
31. Rust, R.T. The future of marketing. *Int. J. of Res. in Marketing* **2020**, *37*, 15–26. https://doi.org/10.1016/j.ijresmar.2019.08.002.
32. Sarin, S.; Singh, S.K.; Kumar, S.; Goyal, S.; Gupta, B.B.; Alhalabi, W.; Arya, V. Unleashing the power of multi-agent reinforcement learning for algorithmic trading in the digital financial frontier and enterprise information systems. *Comput. Mater. Contin.* **2024**, *80*, 3123–3138. https://doi.org/10.32604/cmc.2024.051599.
33. Duan, Y.; Edwards, J.S.; Dwivedi, Y.K. Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *Int. J. Inf. Manag.* **2019**, *48*, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021.
34. Cherradi, M.; Bouhafer, F.; EL Haddadi, A. Data lake governance using IBM-Watson knowledge catalog. *Sci. Afr.* **2023**, *21*, e01854. https://doi.org/10.1016/j.sciaf.2023.e01854.
35. Shrestha, Y.R.; Ben-Menahem, S.M.; von Krogh, G. Organizational decision-making structures in the age of artificial intelligence. *Calif. Manag. Rev.* **2019**, *61*, 66–83. https://doi.org/10.1177/0008125619862257.
36. Portugal, I.; Alencar, P.; Cowan, D. The use of machine learning algorithms in recommender systems: A systematic review. *Expert Syst. Appl.* **2018**, *97*, 205–227. https://doi.org/10.1016/j.eswa.2017.12.020.
37. Zhang, S.; Yao, L.; Sun, A.; Tay, Y. Deep Learning Based Recommender System: A Survey and New Perspectives. *ACM Comput. Surv.* **2019**, *52*. https://doi.org/10.1145/3285029.

38. Ayemowa, M.O.; Ibrahim, R.; Bena, Y.A. A systematic review of the literature on deep learning approaches for cross-domain recommender systems. *Decision Analytics Journal* **2024**, *13*, 100518. https://doi.org/10.1016/j.dajour.2024.100518.
39. Grewal, D.; Noble, S.M.; Roggeveen, A.L.; Nordfält, J. The future of in-store technology. *J. Acad. Mark. Sci.* **2020**, *48*, 96–113. https://doi.org/10.1007/s11747-019-00697-z.
40. Shankar, V. How Artificial Intelligence (AI) is Reshaping Retailing. *J. Retail.* **2018**, *94*, vi–xi. https://doi.org/10.1016/S0022-4359(18)30076-9.
41. Flavián, C.; Ibáñez-Sánchez, S.; Orús, C. The impact of virtual, augmented and mixed reality technologies on the customer experience. *J. Bus. Res.* **2019**, *100*, 547–560. https://doi.org/10.1016/j.jbusres.2018.10.050.
42. Yaqub, M.Z.; Alsabban, A. Industry-4.0-Enabled Digital Transformation: Prospects, Instruments, Challenges, and Implications for Business Strategies. *Sustainability* **2023**, *15*, 8553. https://doi.org/10.3390/su15118553.
43. del Val Núñez, M.T.; de Lucas Ancillo, A.; Gavrila Gavrila, S.; Gómez Gandía, J.A. Technological transformation in HRM through knowledge and training: Innovative business decision making. *Technol. Forecast. Soc. Change* **2024**, *200*, 123168. https://doi.org/10.1016/j.techfore.2023.123168.
44. Stahl, B.C. Responsible innovation ecosystems: Ethical implications of the application of the ecosystem concept to artificial intelligence. *Int. J. Inf. Manag.* **2022**, *62*, 102441. https://doi.org/10.1016/j.ijinfomgt.2021.102441.
45. Daradkeh, F.M.; Hassan, T.H.; Palei, T.; Helal, M.Y.; Mabrouk, S.; Saleh, M.I.; Salem, A.E.; Elshawarbi, N.N. Enhancing Digital Presence for Maximizing Customer Value in Fast-Food Restaurants. *Sustainability* **2023**, *15*, 5690. https://doi.org/10.3390/su15075690.
46. Tawil, A.R.H.; Mohamed, M.; Schmoor, X.; Vlachos, K.; Haidar, D. Trends and Challenges towards Effective Data-Driven Decision Making in UK Small and Medium-Sized Enterprises: Case Studies and Lessons Learnt from the Analysis of 85 Small and Medium-Sized Enterprises. *Big Data Cogn. Comput.* **2024**, *8*, 79. https://doi.org/10.3390/bdcc8070079.
47. Jöhnk, J.; Weißert, M.; Wyrtki, K. Ready or not, AI comes— an interview study of organizational AI readiness factors. *Bus. Inf. Syst. Eng.* **2020**, *63*, 5–20. https://doi.org/10.1007/s12599-020-00676-7.
48. Choung, H.; David, P.; Ross, A. Trust and ethics in AI. *AI & SOC.* **2022**, *38*, 733–745. https://doi.org/10.1007/s00146-022-01473-4.
49. Garbuio, M.; Lin, N. Artificial intelligence as a growth engine for health care startups: Emerging business models. *Calif. Manag. Rev.* **2019**, *61*, 59–83. https://doi.org/10.1177/0008125618811931.
50. Black, S.; Samson, D.; Ellis, A. Moving beyond 'proof points': Factors underpinning AI-enabled business model transformation. *Int. J. Inf. Manag.* **2024**, *77*, 102796. https://doi.org/10.1016/j.ijinfomgt.2024.102796.
51. Sjödin, D.; Parida, V.; Palmié, M.; Wincent, J. How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *J. Bus. Res.* **2021**, *134*, 574–587. https://doi.org/10.1016/j.jbusres.2021.05.009.
52. Jarrahi, M.H. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Bus. Horiz.* **2018**, *61*, 577–586. https://doi.org/10.1016/j.bushor.2018.03.007.
53. Corrêa, N.K.; Galvão, C.; Santos, J.W.; Del Pino, C.; Pinto, E.P.; Barbosa, C.; Massmann, D.; Mambrini, R.; Galvão, L.; Terem, E.; et al. Worldwide AI ethics: A review of 200 guidelines and recommendations for AI governance. *Patterns (N. Y.)* **2023**, *4*, 100857. https://doi.org/10.1016/j.patter.2023.100857.
54. Sjödin, D.; Parida, V.; Kohtamäki, M. Artificial intelligence enabling circular business model innovation in digital servitization: Conceptualizing dynamic capabilities, AI capacities, business models and effects. *Technol. Forecast. Soc. Change* **2023**, *197*, 122903. https://doi.org/10.1016/j.techfore.2023.122903.
55. Nambisan, S.; Baron, R.A. On the costs of digital entrepreneurship: Role conflict, stress, and venture performance in digital platform-based ecosystems. *J. Bus. Res.* **2021**, *125*, 520–532. https://doi.org/10.1016/j.jbusres.2019.06.037.
56. Mancuso, I.; Messeni Petruzzelli, A.; Panniello, U. Digital business model innovation in metaverse: How to approach virtual economy opportunities. *Inf. Process. Manag.* **2023**, *60*, 103457. https://doi.org/10.1016/j.ipm.2023.103457.
57. Jorzik, P.; Klein, S.P.; Kanbach, D.K.; Kraus, S. AI-driven business model innovation: A systematic review and research agenda. *J. Bus. Res.* **2024**, *182*, 114764. https://doi.org/10.1016/j.jbusres.2024.114764.

58. Saleem, I.; Al-Breiki, N.S.S.; Asad, M. The nexus of artificial intelligence, frugal innovation and business model innovation to nurture internationalization: A survey of SME's readiness. *J. Open Innov.* **2024**, *10*, 100326. https://doi.org/10.1016/j.joitmc.2024.100326.
59. Jelenčič, J.; Massri, M.B.; Grobelnik, M.; Mladenić, D. A Multilingual Approach to Analyzing Talent Demand in a Specific Domain: Insights From Global Perspectives on Artificial Intelligence Talent Demand. *IEEE Access* **2024**, *12*, 80115–80127. https://doi.org/10.1109/ACCESS.2024.3409577.
60. Ridzuan, N.N.; Masri, M.; Anshari, M.; Fitriyani, N.L.; Syafrudin, M. AI in the Financial Sector: The Line between Innovation, Regulation and Ethical Responsibility. *Information* **2024**, *15*, 432. https://doi.org/10.3390/info15080432.
61. Lamperti, F. Unlocking machine learning for social sciences: The case for identifying Industry 4.0 adoption across business restructuring events. *Technol. Forecast. Soc. Change* **2024**, *207*, 123627. https://doi.org/10.1016/j.techfore.2024.123627.
62. Pistrui, B.; Kostyal, D.; Matyusz, Z. Dynamic acceleration: Service robots in retail. *Cogent Bus. Manag.* **2023**, *10*. https://doi.org/10.1080/23311975.2023.2289204.
63. Pantanowitz, L.; Hanna, M.; Pantanowitz, J.; Lennerz, J.; Henricks, W.H.; Shen, P.; Quinn, B.; Bennet, S.; Rashidi, H.H. Regulatory Aspects of Artificial Intelligence and Machine Learning. *Mod. Pathol.* **2024**, *37*, 100609. https://doi.org/10.1016/j.modpat.2024.100609.
64. Mehrabi, N.; Morstatter, F.; Saxena, N.; Lerman, K.; Galstyan, A. A survey on bias and fairness in machine learning. *ACM Computing Surveys (CSUR)* **2021**, *54*, 1–35. https://doi.org/10.1145/3457607.
65. Ntoutsi, E.; Fafalios, P.; Gadiraju, U.; Iosifidis, V.; Nejdl, W.; Vidal, M.E.; others.; Staab, S. Bias in data-driven artificial intelligence systems—An introductory survey. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2020**, *10*, e1356. https://doi.org/10.1002/widm.1356.
66. Chen, Z. Ethics and discrimination in artificial intelligence-enabled recruitment practices. *Humanit. Soc. Sci. Commun.* **2023**, *10*. https://doi.org/10.1057/s41599-023-02079-x.
67. Fuster, A.; Goldsmith-Pinkham, P.; Ramadorai, T.; Walther, A. Predictably Unequal? The Effects of Machine Learning on Credit Markets. *J. Finance* **2021**, *77*, 5–47. https://doi.org/10.1111/jofi.13090.
68. Kaplan, A.; Haenlein, M. Rulers of the world, unite! The challenges and opportunities of artificial intelligence. *Bus. Horiz.* **2020**, *63*, 37–50. https://doi.org/10.1016/j.bushor.2019.09.003.
69. Adadi, A.; Berrada, M. Peeking inside the black-box: A survey on explainable artificial intelligence (XAI). *IEEE Access* **2018**, *6*, 52138–52160. https://doi.org/10.1109/ACCESS.2018.2870052.
70. Rudin, C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nat. Mach. Intell.* **2019**, *1*, 206–215. https://doi.org/10.1038/s42256-019-0048-x.
71. Arrieta, A.B.; Díaz-Rodríguez, N.; Del Ser, J.; Bennetot, A.; Tabik, S.; Barbado, A.; others.; Herrera, F. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion* **2020**, *58*, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012.
72. Frank, M.R.; Autor, D.; Bessen, J.E.; Brynjolfsson, E.; Cebrian, M.; Deming, D.J.; others.; Rahwan, I. Toward understanding the impact of artificial intelligence on labor. *Proc. Natl. Acad. Sci. U. S. A.* **2019**, *116*, 6531–6539. https://doi.org/10.1073/pnas.1900949116.
73. Jobin, A.; Ienca, M.; Vayena, E. The global landscape of AI ethics guidelines. *Nat. Mach. Intell.* **2019**, *1*, 389–399. https://doi.org/10.1038/s42256-019-0088-2.
74. Cath, C.; Wachter, S.; Mittelstadt, B.; Taddeo, M.; Floridi, L. Artificial intelligence and the 'good society': the US, EU, and UK approach. *Sci. Eng. Ethics* **2018**, *24*, 505–528. https://doi.org/10.1007/s11948-017-9901-7.
75. Vakkuri, V.; Kemell, K.K.; Kultanen, J.; Abrahamsson, P. The current state of industrial practice in artificial intelligence ethics. *IEEE Software* **2020**, *37*, 50–57. https://doi.org/10.1109/MS.2020.2985621.
76. Aïvodji, U.; Bidet, F.; Gambs, S.; Ngueveu, R.C.; Tapp, A. Local Data Debiasing for Fairness Based on Generative Adversarial Training. *Algorithms* **2021**, *14*, 87. https://doi.org/10.3390/a14030087.
77. Wan, M.; Zha, D.; Liu, N.; Zou, N. In-Processing Modeling Techniques for Machine Learning Fairness: A Survey. *ACM Trans. Knowl. Discov. Data* **2023**, *17*, 1–27. https://doi.org/10.1145/3551390.
78. Yang, Q.; Liu, Y.; Chen, T.; Tong, Y. Federated machine learning: Concept and applications. *ACM Trans. Intell. Syst. Technol.* **2019**, *10*, 1–19. https://doi.org/10.1145/3298981.
79. Torkzadehmahani, R.; Nasirigerdeh, R.; Blumenthal, D.B.; Kacprowski, T.; List, M.; Matschinske, J.; Spaeth, J.; Wenke, N.K.; Baumbach, J. Privacy-Preserving Artificial Intelligence Techniques in Biomedicine. *Methods Inf. Med.* **2022**, *61*, e12–e27. https://doi.org/10.1055/s-0041-1740630.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 19 February 2025 doi:10.20944/preprints202502.1465.v1

80. Mirzaei, S.; Mao, H.; Al-Nima, R.R.O.; Woo, W.L. Explainable AI Evaluation: A Top-Down Approach for Selecting Optimal Explanations for Black Box Models. *Information* **2023**, *15*, 4. https://doi.org/10.3390/info15010004.
81. Linardatos, P.; Papastefanopoulos, V.; Kotsiantis, S. Explainable AI: A Review of Machine Learning Interpretability Methods. *Entropy* **2020**, *23*, 18. https://doi.org/10.3390/e23010018.
82. Mökander, J.; Floridi, L. Ethics-Based Auditing to Develop Trustworthy AI. *Minds and Machines* **2021**, *31*, 323–327. https://doi.org/10.1007/s11023-021-09557-8.
83. Dignum, V. Ethics in artificial intelligence: Introduction to the special issue. *Ethics Inf. Technol.* **2018**, *20*, 1–3. https://doi.org/10.1007/s10676-018-9450-z.
84. Grosz, B.J.; Grant, D.G.; Vredenburgh, K.; Behrends, J.; Hu, L.; Simmons, A.; Waldo, J. Embedded EthiCS: Integrating ethics across CS education. *Commun. ACM* **2019**, *62*, 54–61. https://doi.org/10.1145/3330794.
85. Vinuesa, R.; Azizpour, H.; Leite, I.; Balaam, M.; Dignum, V.; Domisch, S.; others.; Nerini, F.F. The role of artificial intelligence in achieving the Sustainable Development Goals. *Nat. Commun.* **2020**, *11*, 1–10. https://doi.org/10.1038/s41467-019-14108-y.
86. Nishant, R.; Kennedy, M.; Corbett, J. Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *Int. J. Inf. Manag.* **2020**, *53*, 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104.
87. Dellermann, D.; Ebel, P.; Söllner, M.; Leimeister, J.M. Hybrid intelligence. *Bus. Inf. Syst. Eng.* **2019**, *61*, 637–643. https://doi.org/10.1007/s12599-019-00595-2.
88. Seeber, I.; Bittner, E.; Briggs, R.O.; de Vreede, T.; de Vreede, G.J.; Elkins, A.; others.; Söllner, M. Machines as teammates: A research agenda on AI in team collaboration. *Inf. Manag.* **2020**, *57*, 103174. https://doi.org/10.1016/j.im.2019.103174.
89. Berretta, S.; Tausch, A.; Ontrup, G.; Gilles, B.; Peifer, C.; Kluge, A. Defining human-AI teaming the human-centered way: a scoping review and network analysis. *Front. Artif. Intell.* **2023**, *6*. https://doi.org/10.3389/frai.2023.1250725.
90. Ahmed, S.; Shahzad, K. Augmenting Business Process Model Elements With End-User Feedback. *IEEE Access* **2022**, *10*, 115635–115651. https://doi.org/10.1109/access.2022.3216418.
91. Kolomaznik, M.; Petrik, V.; Slama, M.; Jurik, V. The role of socio-emotional attributes in enhancing human-AI collaboration. *Front. Psychol.* **2024**, *15*. https://doi.org/10.3389/fpsyg.2024.1369957.
92. van Dijk, W.; Baltrusch, S.J.; Dessers, E.; de Looze, M.P. The effect of human autonomy and robot work pace on perceived workload in human-robot collaborative assembly work. *Front. Robot. AI.* **2023**, *10*. https://doi.org/10.3389/frobt.2023.1244656.
93. Galland, L.; Pelachaud, C.; Pecune, F. Adapting conversational strategies in information-giving human-agent interaction. *Front. Artif. Intell.* **2022**, *5*. https://doi.org/10.3389/frai.2022.1029340.
94. Bai, S.; Yu, D.; Han, C.; Yang, M.; Gupta, B.B.; Arya, V.; Panigrahi, P.K.; Tang, R.; He, H.; Zhao, J. Warmth trumps competence? Uncovering the influence of multimodal AI anthropomorphic interaction experience on intelligent service evaluation: Insights from the high-evoked automated social presence. *Technol. Forecast. Soc. Change* **2024**, *204*, 123395. https://doi.org/10.1016/j.techfore.2024.123395.
95. Jauhiainen, J.S. The Metaverse: Innovations and generative AI. *Int. J. Innov. Stud.* **2024**, *8*, 262–272. https://doi.org/10.1016/j.ijis.2024.04.004.
96. Mazarakis, A.; Bernhard-Skala, C.; Braun, M.; Peters, I. What is critical for human-centered AI at work? – Toward an interdisciplinary theory. *Front. Artif. Intell.* **2023**, *6*. https://doi.org/10.3389/frai.2023.1257057.
97. Connell, A.; Montgomery, H.; Martin, P.; Nightingale, C.; Sadeghi-Alavijeh, O.; King, D.; others.; Raine, R. Evaluation of a digitally-enabled care pathway for acute kidney injury management in hospital emergency admissions. *NPJ Digital Medicine* **2019**, *2*, 1–9. https://doi.org/10.1038/s41746-019-0100-6.
98. Fares, O.H.; Butt, I.; Lee, S.H.M. Utilization of artificial intelligence in the banking sector: a systematic literature review. *J. Financ. Serv. Mark.* **2022**, *28*, 835–852. https://doi.org/10.1057/s41264-022-00176-7.
99. Huang, T.; Safranek, C.; Socrates, V.; Chartash, D.; Wright, D.; Dilip, M.; Sangal, R.B.; Taylor, R.A. Patient-Representing Population's Perceptions of GPT-Generated Versus Standard Emergency Department Discharge Instructions: Randomized Blind Survey Assessment. *J. Med. Internet Res.* **2024**, *26*, e60336. https://doi.org/10.2196/60336.
100. Cancela-Outeda, C. The EU's AI act: A framework for collaborative governance. *Internet Things (Neth.)* **2024**, *27*, 101291. https://doi.org/10.1016/j.iot.2024.101291.
101. Sun, W.; Tohirovich Dedahanov, A.; Li, W.P.; Young Shin, H. Sanctions and opportunities: Factors affecting China's high-tech SMEs adoption of artificial intelligence computing leasing business. *Heliyon* **2024**, *10*, e36620. https://doi.org/10.1016/j.heliyon.2024.e36620.

102. Chatterjee, S.; Rana, N.P.; Dwivedi, Y.K. How does business analytics contribute to organisational performance and business value? A resource-based view. *Inf. Technol. People* **2021**, *34*, 736–764. https://doi.org/10.1108/ITP-08-2020-0603.
103. Ghobakhloo, M.; Iranmanesh, M.; Grybauskas, A.; Vilkas, M.; Petraitė, M. Industry 4.0, innovation, and sustainable development: A systematic review and a roadmap to sustainable innovation. *Bus. Strategy Environ.* **2021**, *30*, 2013–2032. https://doi.org/10.1002/bse.2867.
104. Schwaeke, J.; Peters, A.; Kanbach, D.K.; Kraus, S.; Jones, P. The new normal: The status quo of AI adoption in SMEs. *J. Small Bus. Manag.* **2024**, *0*, 1–35. https://doi.org/10.1080/00472778.2024.2379999.
105. Oldemeyer, L.; Jede, A.; Teuteberg, F. Investigation of artificial intelligence in SMEs: a systematic review of the state of the art and the main implementation challenges. *Manag. Rev. Q.* **2024**. https://doi.org/10.1007/s11301-024-00405-4.