The Impact of AI Adoption on Productivity Across FinTech, Retail, and Advanced Manufacturing:

A Systematic Quantitative Literature Review Approach

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Abstract

This paper explores how artificial intelligence (AI) adoption impacts firm-level productivity across FinTech, Retail, and Advanced Manufacturing sectors, using a systematic quantitative literature review and corporate 10-K filings. Drawing on an extensive literature review of 150+ peer-reviewed academic papers and 30 corporate annual reports, the research synthesizes key trends and benefits in AI adoption, its productivity implications, and associated challenges and barriers.

The findings reveal that there is a predominantly positive outlook in prior literature regarding AI's impact on firms and its associated business processes, but that there is substantial debate and concern about appropriate productivity measures and the nature of AI's socioeconomic implications and challenges. Moreover, AI adoption generally correlates with productivity improvements, particularly through automation, predictive analytics, and customer personalisation.

However, sector-specific challenges, such as trust in retail AI systems, skill gaps in manufacturing, and regulatory uncertainty in FinTech, could affect diffusion and workforce resilience. Consequently, the paper concludes with policy recommendations for responsible and inclusive AI deployment, aligned with the UK AI Opportunities Action Plan, and aligns the findings with the OECD's AI input-output framework.

Table of Contents

1. INTRODUCTION

In recent years, Artificial Intelligence (AI) has been regarded as a new general-purpose technology with rapid, penetrating, and wide-reaching applications for a wide range of industrial sectors (Agrawal, Gans and Goldfarb, 2019; Brynjolfsson, Rock and Syverson, 2019). Generally, general-purpose technology is defined as the ability to implement new and complementary production methods that may increase productivity over time (Bresnahan and Trajtenberg, 1995; Bresnahan *et al.*, 2002; Brynjolfsson and Hitt, 2005; Cardona, Kretschmer and Strobel, 2013). Therefore, it is reasonable to assume that the adoption of AI technologies would enact new business opportunities and boost productivity (Brynjolfsson and McAfee, 2014). Since the advantages associated with AI development and implementation are primarily reaped by market leaders and early adopters (Czarnitzki, Fernández and Rammer, 2023), deploying AI may further widen the productivity gap between companies. Such companies can exploit first-mover advantages, increasing their dynamic returns (Igna and Venturini, 2023). Despite this, AI and other breakthrough technologies may offer new opportunities for businesses to restructure and improve productivity, thus allowing them to better compete with industry leaders (Igna and Venturini, 2023; Shuai Wang *et al.*, 2024; Li *et al.*, 2025).

Considering the FinTech sector, AI's advanced data processing, pattern recognition, and predictive analytics optimize investment strategies and improve financial institutions' efficiency, offering broad application prospects (Holzinger *et al.*, 2023). In the retail sector, AI is revolutionizing consumer experiences through demand forecasting, personalized recommendations, and the integration of online and offline operations, reshaping traditional shopping models and boosting operational efficiency, primarily due to the COVID-19 outbreak (Shankar *et al.*, 2021a; Yeh *et al.*, 2022). Meanwhile, in advanced manufacturing, especially the construction industry, AI-driven automation, predictive maintenance, and process optimization improve productivity and competitiveness, addressing challenges such as cost overruns and production delays (Yigitcanlar and Cugurullo, 2020; Yigitcanlar, 2021). However, despite its promises, AI integration presents multiple challenges, including regulatory uncertainty in frameworks, data security issues, skill gaps, workforce upskilling, and cost-related constraints. Moreover, two distinct characteristics of AI make economic analysis unique from prior breakthroughs in the field. First, AI is an intangible technology, which makes it difficult to measure its impact and determine its true economic significance (Haskel and Westlake, 2018). The second difference between AI and other technologies is the range of its applications because AI can carry out a wide range of cognitive tasks usually performed by highly skilled workers (Brynjolfsson and McAfee, 2017; Corrado et al., 2021a). Despite AI's potential to enhance worker productivity, improve production efficiency, and drive product/service development, the existing literature remains fragmented. Most studies examine AI adoption within single industries, focus selectively on either technological opportunities or barriers, or provide descriptive insights without systematically linking AI to firm-level productivity outcomes. In addition, robust empirical evidence or longitudinal studies of sustained productivity

improvements and clear paths for workforce transitions remain limited. While systematic literature reviews are common, combining them with 10K filings provides a less explored and novel perspective on how firms define and measure AI adoption and its impact on productivity. Therefore, this gap is critical, as the full economic and social benefits of AI adoption across these sectors depend on successfully defining and navigating the terms of AI adoption and their interconnections with productivity metrics and workforce-related challenges.

To address this gap, this study systematically examines the current evidence and definitions on AI adoption's productivity impacts across three pivotal sectors: FinTech, Retail, and Advanced Manufacturing. By conducting a systematic quantitative literature review of more than 150 empirical studies, financial and annual reports, and bibliometric analyses, this research aims to examine how AI adoption influences productivity outcomes across different industries, identify key thematic trends, benefits, and challenges associated with AI adoption, and provide valuable insights for policymakers, industry leaders, and academic researchers.

Specifically, the study addresses critical interlinked research questions:

- How does AI adoption influence productivity across FinTech, Retail, and Advanced Manufacturing?
- How do firms across these sectors navigate AI adoption regulatory, ethical, and workforce-related challenges?

By addressing these questions, the study contributes to the ongoing debate on AI's adoption impact in defining the productivity gains and providing critical insights to mitigate potential workforce displacement and promote inclusive productivity growth.. This paper is structured as follows: Section 2 details the methodology, describing the systematic quantitative literature review approach and bibliometric analysis. Section 3 presents the key findings, while Section 4 discusses the policy implications. Finally, Section 5 concludes the study, offering directions for future research and industry considerations.

2. METHODOLOGY AND DATA

We conducted a thorough search of the topic area and employed a systematic quantitative literature review technique to review and assess the relevant literature in the AI area, consistent with previous scientific works (Zupic and Čater, 2015; Fisch and Block, 2018). The data for this study was collected by gathering documents from two significant databases: Scopus and Web of Science (WOS). These two primary sources of data were adopted because they compile a set of the most relevant scientific outputs in the fields of business and management, social sciences, and managerial finance. Both databases enable the organization and integration of data gathered from various academic peer-reviewed journal articles in ready-to-use bibliometric formats. Thus, this study followed a PRISMA protocol for selecting relevant literature to offer replicability to the research by focusing on the three stages of identification, screening, and inclusion. We

created a research structure that was categorized under three overarching themes: AI adoption, productivity metrics, and challenges and barriers for each sector. Next, we complement our methodology by selecting, downloading, and reviewing 10-k reports from major firms across the three sectors to identify, define, and assess the definitions of AI adoption and technologies and how they impact their current or future productivity plans. Finally, a bibliometric analysis was conducted to perform a keyword co-occurrence analysis and a thematic analysis to create clusters and themes considering our research objective. We used the software research tools NVIVO and VosViewer to execute the thematic coding and bibliometric analysis.

First, we conducted a keyword search in the Scopus and Web of Science databases, encompassing publication years from 2018 to 2025, targeting journal articles exclusively in English. We used tailored keywords specific to each sector to ensure thematic relevance. The first figure highlights the protocol that we followed for our study. To begin, we searched the Scopus database for titles, abstracts, and keywords containing the terms "AI," "artificial intelligence," and other keywords that cover AI subfields such as "machine learning" and different types of productivity, including "performance", "efficiency", and "productivity". Specifically, for the FinTech sector, keywords included AI-related terms combined with productivity, performance, and efficiency, alongside industry-specific terms such as blockchain and digital banking, yielding 433 papers. The Retail sector incorporated keywords focusing on AI adoption, machine learning, customer experience, smart retail, and inventory management, generating 365 papers. The Advanced Manufacturing sector employed keywords related to AI adoption, smart manufacturing, advanced manufacturing, and firm performance, resulting in 695 papers. Following this initial retrieval, a rigorous selection process based on subject areas—including Business, Management, Accounting, Social Sciences, Economics, Econometrics, Finance, and Decision Sciences—was applied, narrowing down to a population database comprising a total of 1,493 papers across all sectors. Further refinement through a detailed review of titles and abstracts led to the selection of 75 retail papers, 71 FinTech papers, and 145 manufacturing papers. Subsequent evaluations of the introduction and conclusion facilitated a final download of 69 retail, 68 FinTech, and 84 manufacturing papers. These documents underwent a thorough thematic analysis using NVivo, culminating in the detailed examination of 52 papers for Retail, 58 for FinTech, and 64 for Advanced Manufacturing, because of access problems of the papers in NVIVO, forming the final sample for analysis. Lastly, we extracted metadata for the documents included in the final sample, including titles, number of citations, keywords, affiliations, and countries. Moreover, the complete keyword queries used in Scopus searches are provided in Appendix A (Figure A2) for transparency and replicability for future research.

In addition to academic literature, the study searched and analyzed 10-K annual reports from leading firms across the three sectors, selected based on company relevance, public availability, and the frequency of AI-related disclosures or keywords that matched the initial selection criteria. Therefore, the sample was based on large publicly traded firms such as Amazon, Siemens, Visa, and Boeing. Although the study is aware of the likelihood of selection bias, the

different perspectives of small or medium privately held companies are not included. Finally, the findings from the 10-K annual reports should be highlighted as an indicator of leading industry case studies rather than a representative reflection of all firms across the three sectors.

Then, we utilized the VOSviewer software to support the bibliometric analysis by generating keyword co-occurrence maps and cluster visualizations, which identified thematic clusters across sectors. In addition, to construct the keyword co-occurrence networks, the association strength normalization method was applied. This approach adjusts for differences in raw keyword frequency, ensuring that co-occurrence strengths are not inflated simply because a term appears frequently in the dataset. Moreover, full counting was employed, meaning that each co-occurrence between two terms was counted once per document, regardless of how many times the terms appeared within the same article, unlike the binary method. Next, clustering was performed with VOSviewer's default algorithm, using a minimum threshold of five co-occurrences per keyword. Regarding the visualization, the "no overlap" display option was activated to enhance readability through the network visualization application. In the resulting maps, node size corresponds to the frequency of a keyword, while edge thickness reflects the relative strength of its co-occurrence with other terms. The identified clusters highlight thematic groupings across the literature, providing an overview of how AI adoption and productivity are interconnected within each sector.

Simultaneously, to complement the bibliometric maps, word clouds were generated in NVivo 15. These visualizations display the 100 most frequently occurring words in each sector's corpus after removing common stop words and irrelevant terms such as "paper", "study", "author", and "year". A minimum threshold of five mentions across the dataset was applied to ensure that only substantively relevant words remained in the analysis. In the word clouds, the relative size of each word reflects its overall frequency, offering a quick overview of concepts related to productivity, workforce challenges, and sectoral themes. To complement the visualizations, frequency tables of the top terms were exported from NVivo and are reported in Appendix B to provide quantitative information for each sector. While word clouds are descriptive rather than analytical, they serve as an accessible way to highlight dominant ideas and were interpreted alongside the VOSviewer maps to strengthen the sectoral synthesis. The three methodological choices of this study have been highlighted to complement one another, presenting them as a holistic approach. Thus, these methodological approaches allowed both an initial mapping of the field and a deeper sectoral understanding, while providing academic insights into firm-level discourse.

To conclude this section, this specific methodology is limited by potential publication bias (toward positive AI outcomes), variation in financial reporting standards, and limited access to

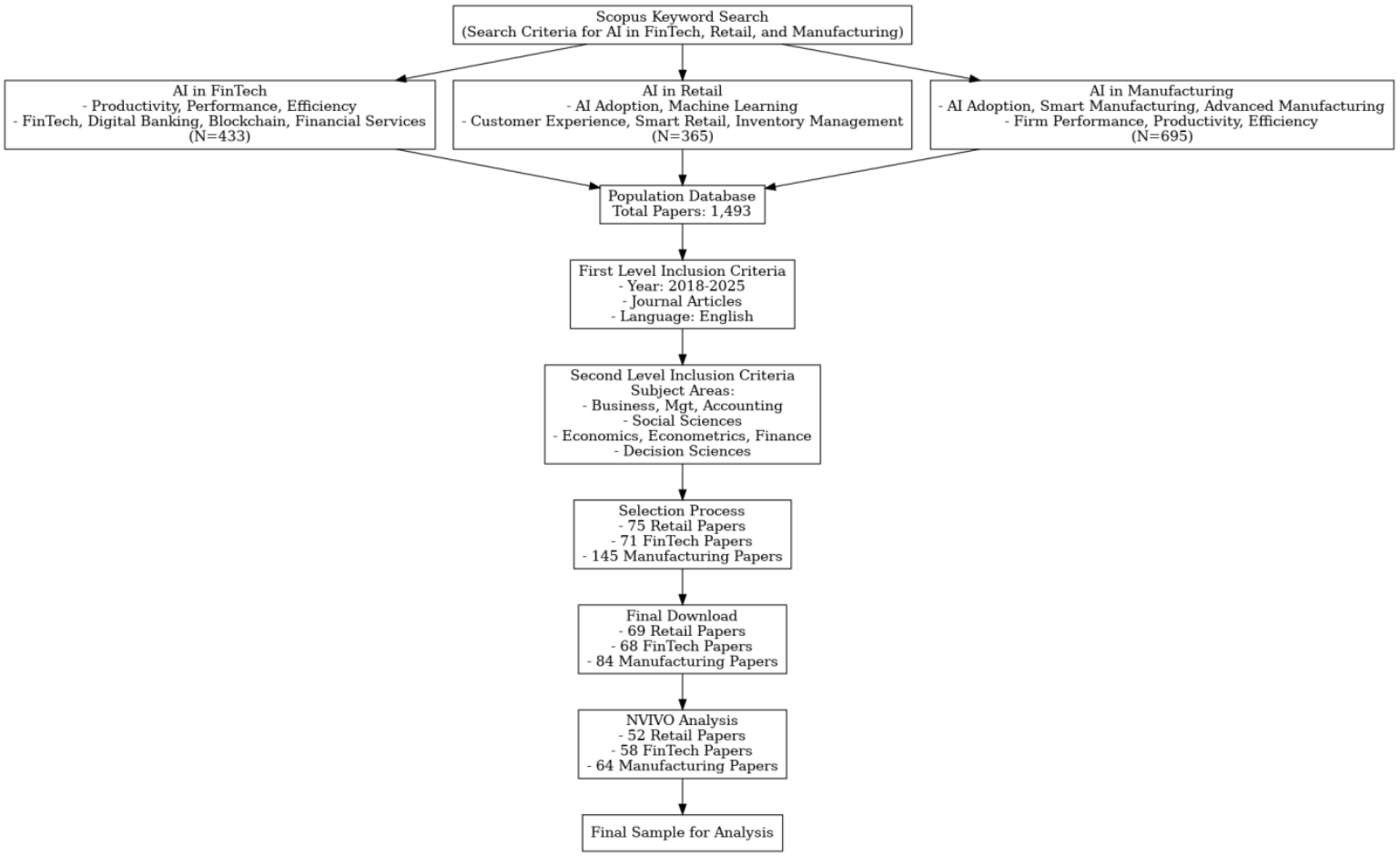

Fig. 1. Research Protocol details of the study on AI in Productivity. Notes: 1) Data was retrieved in November 2024; 2) AI was searched using multiple keywords similar for each sector to avoid selection bias, including "artificial intelligence", related keywords of "machine learning", "deep learning", "big data", "robot", "automation", "natural language processing". The main focus is on AI adoption.

SME data due to 10-K constraints and the non-IPO companies' plan. However, triangulating academic and firm-level sources helps mitigate some of the potential risks. To expand our limitations section, the bibliometric data from journal articles are prone to publication bias, because most of the studies demonstrated positive outcomes of AI adoption due to the higher chances of being published. Second, as mentioned before, we relied on 10-K annual reports of large publicly traded firms without taking into consideration the differences of smaller or non-listed companies. Third, the VOSviewer analysis implemented association strength normalization to scale link weights by keyword co-occurrence relevance, but the study did not employ a more advanced network analysis such as centrality to deepen further the insights. Therefore, future research can provide in depth analysis by employing the advanced network analysis techniques to examine connection strengths than only co-occurrence frequencies.

Finally, the nature of the word clouds created by NVivo represent a descriptive analysis of thematic clusters than in depth analytical clusters of definitive measurements about AI adoption.

3. RESULTS AND DISCUSSION

3.1 Descriptive Analysis

We tracked the evolution of publications on the topics of Artificial intelligence and productivity from 2018 to early 2025, which illustrates a growing scholarly interest in artificial intelligence (AI) adoption within FinTech, Retail, and Advanced Manufacturing sectors. The following figures demonstrate population research outputs that have significantly increased over time, with a marked peak in 2024 across all sectors, suggesting heightened academic attention or perhaps critical technological breakthroughs in that period. The rapid growth in the number of articles might be considered somehow normal and physiological, given that we are focusing on a nascent research stream. Specifically, the Advanced Manufacturing sector demonstrates the most considerable cumulative research volume (771 documents), followed by FinTech (502 documents) and Retail (408 documents). The recent decline in document counts in 2025 might reflect publication lag, ongoing research cycles, or shifting research priorities. This trend analysis underscores the necessity of ongoing, sector-specific explorations into AI's productivity impacts, given its dynamic nature and evolving implications for workforce management and technological adoption.

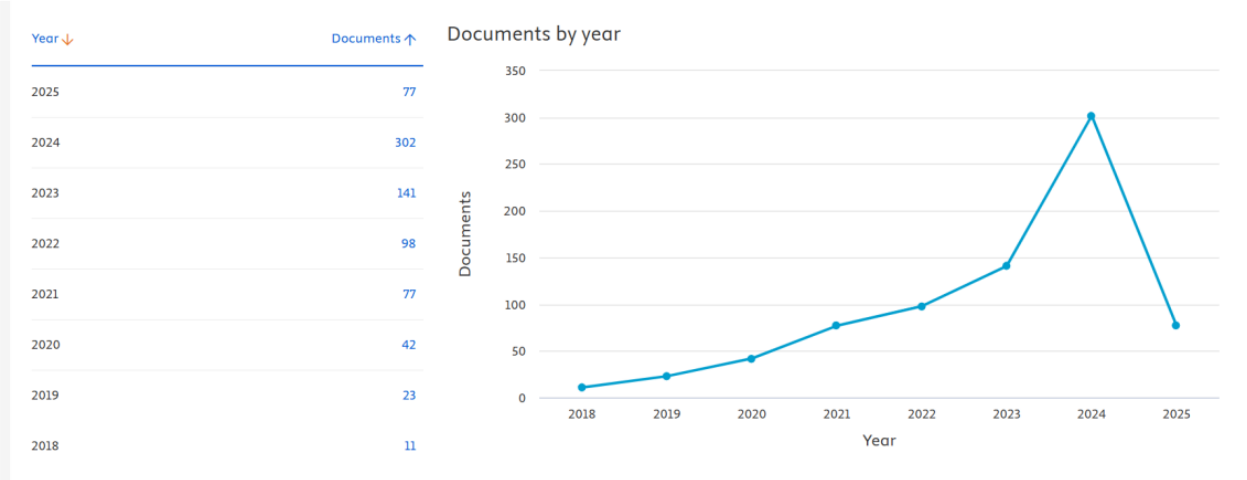

Fig.2. Publications per Year- Adv. Manufacturing Sector

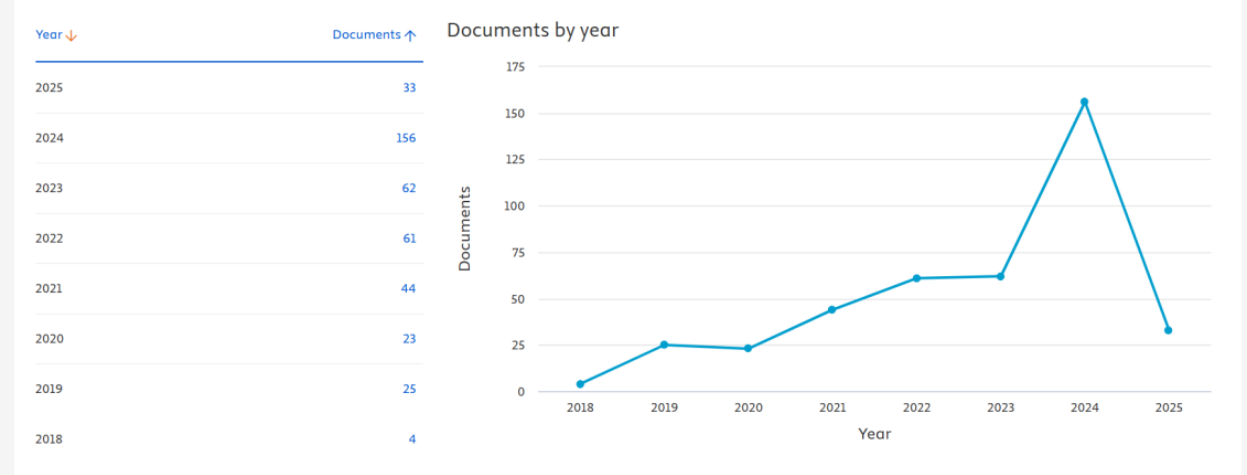

Fig.3. Publications per Year- Retail Sector

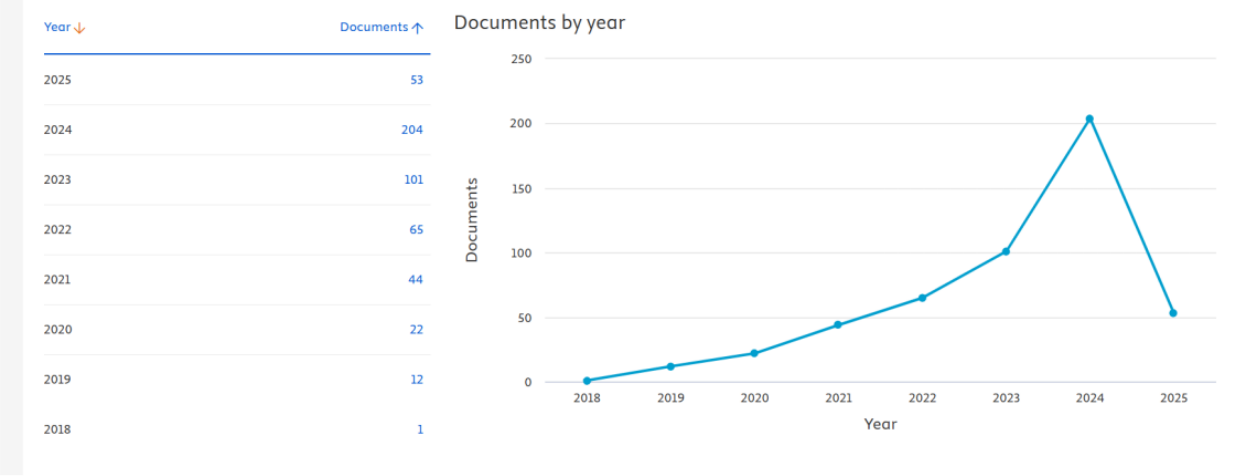

Fig.4. Publications per Year- FinTech Sector

3.2 Keyword Co-Occurrence Analysis

The technique of keyword co-occurrence analysis was implemented to unveil the connections among conceptual items and topics. Specifically, this technique helps us to assume that terms that appear simultaneously are connected through a thematic and topic modelling relationship. Additionally, we represent the progression and the summary of the conceptual items and keywords. Notably, Figures 5, 6, and 7 demonstrate the most frequent words for each sector and their linkages to other words. In addition, the keywords with the highest occurrence in each keyword co-occurrence network were deployed to label the keyword co-occurrence networks. We present here the most frequent words for each sector, as shown in the figures below: for the Fintech: artificial intelligence, machine learning, blockchain, robo-advisors, internet of things. For the retail: artificial intelligence, machine learning, trust, customer experience, e-commerce. For the advanced manufacturing: artificial intelligence, Smart manufacturing, digitalization, green innovation, and big data.

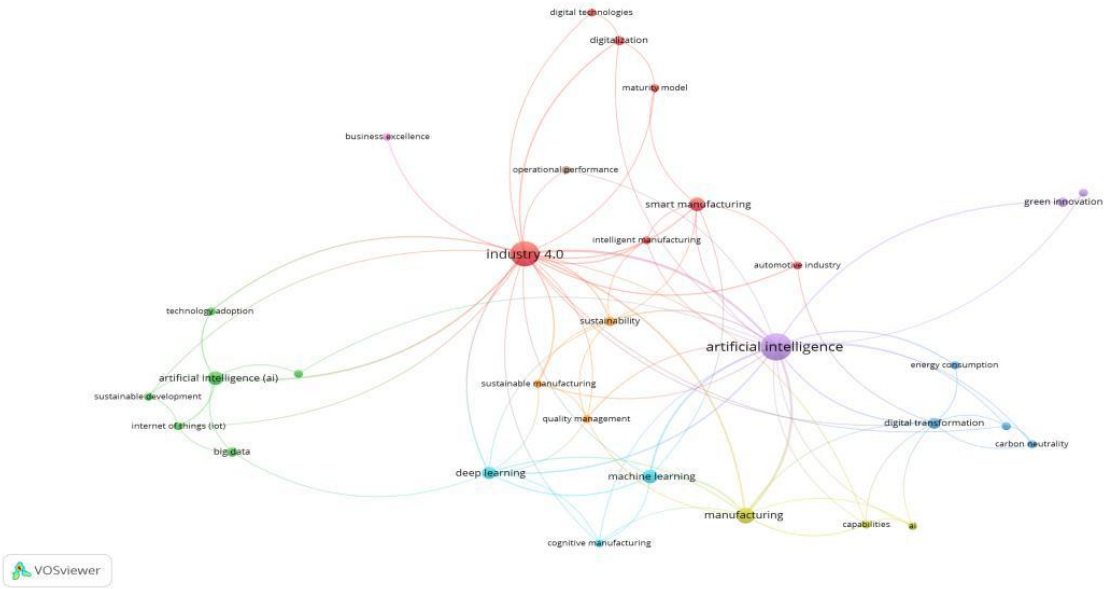

Fig.5. Keyword Co-occurrence- Adv. Manufacturing Sector (VOSviewer)

Note: Nodes represent keywords extracted from publication titles and abstracts related to advanced manufacturing and AI. Node size indicates keyword frequency, and edge thickness reflects co-occurrence strength across articles. Clusters (shown by color) were generated using association strength normalization the "no overlap" setting was applied to improve label readability.

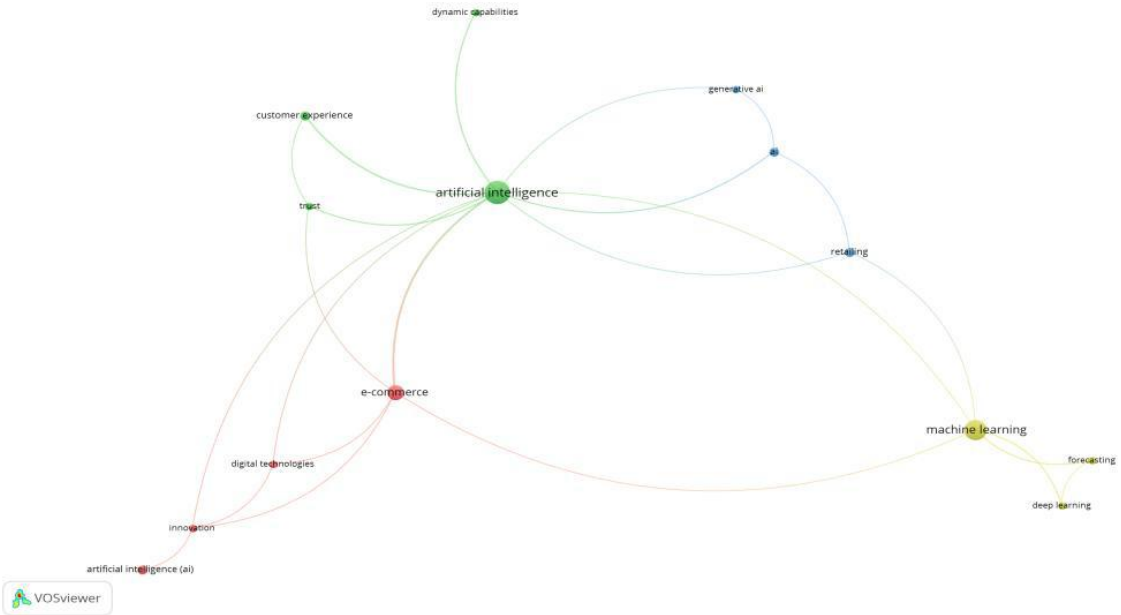

Fig.6. Keyword Co-occurrence- Retail Sector

Note: This map visualizes co-occurring keywords in AI-related retail journal articles. Larger nodes represent more frequently occurring terms, while thicker connecting lines show stronger co-occurrence relationships. Cluster colors

denote thematic groupings (e.g., machine learning, customer experience, e-commerce). Association strength normalization was used, and label overlap was disabled to enhance clarity.

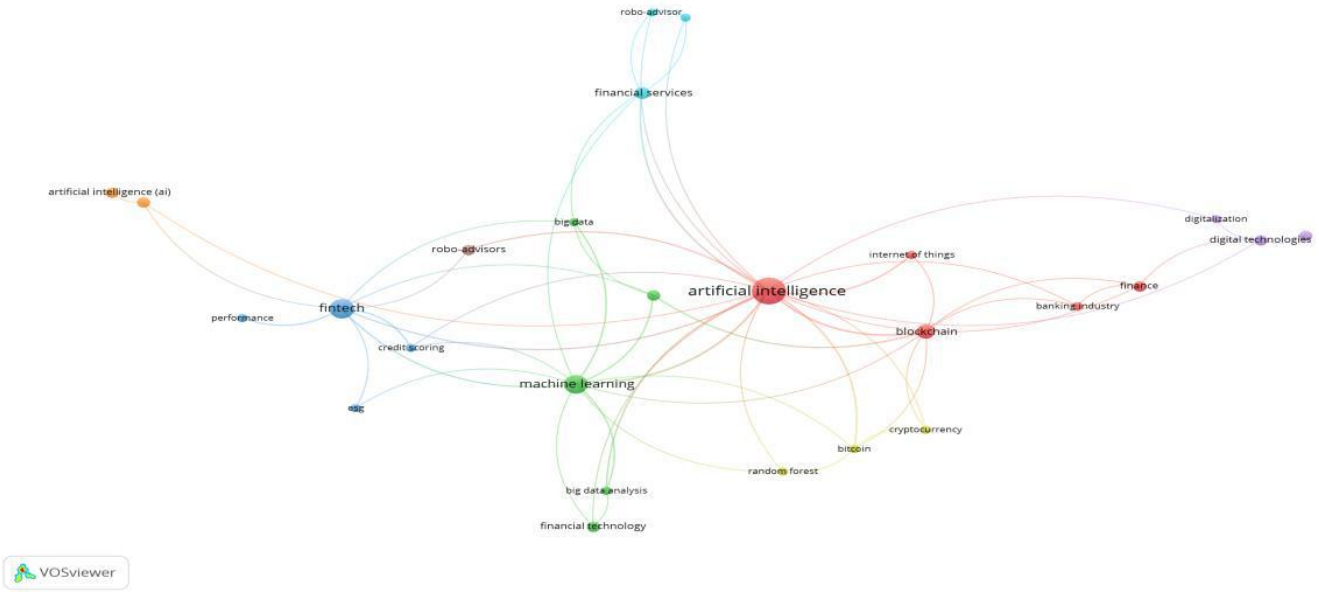

Fig.7. Keyword Co-occurrence- FinTech Sector

Note: Frequent keywords such as "blockchain," "robo-advisor," and "internet of things" are highlighted in this network of AI-focused FinTech literature. Node sizes correspond to term frequency, and edges reflect co-occurrence strength. Visual clusters show thematic concentrations using the association strength method. The layout was optimized the "no overlap" display feature enabled.

3.3 Sector Synthesis and Analysis

To deepen our sectoral synthesis and analysis, this paper draws insights from the OECD's working paper "AI systems in a production function view: inputs and outputs" framework (OECD, 2024). This framework analyzes how AI adoption affects productivity by identifying key dimensions that characterize economic features and implications. The reason for adopting this framework stems from the paper's focus on productivity implications and how AI adoptions through AI systems can be considered a type of production technology. For instance, AI systems are identified as combining intangible inputs (software, skills, data) and computing capacity to produce a range of outputs (analytical tasks like prediction, recommendations, or optimization; content generation and physical tasks in association with robotics). Later in this section, we will implement this framework for each sector to enable a more structured understanding of the specific themes and challenges to AI-driven productivity across the FinTech, Retail, and Advanced Manufacturing sectors.

FinTech Sector

Themes and Insights: The density map analysis of Figure 8, generated by VOS viewer, illustrates critical research themes and insights in the context of AI adoption within the FinTech sector. The density map deployed a text analysis by focusing on the titles and abstracts of every paper in our final sample. Notably, the strong prominence of terms such as "service," "adoption," and "robo advisor" highlights the industry's primary focus on customer-oriented innovation, particularly the enhancement of financial services through personalized and automated advisory platforms. Additionally, the significant presence of "blockchain," "digital transformation," and "digitalization" underscores the integration of AI with distributed ledger technologies, aiming to advance efficiency, transparency, and security in financial transactions and infrastructure. Concurrently, themes like "algorithm," "investor," and "relationship" suggest a strong dependence on algorithmic analytics to facilitate sophisticated decision-making processes and to strengthen client relationships through enhanced predictive capabilities.

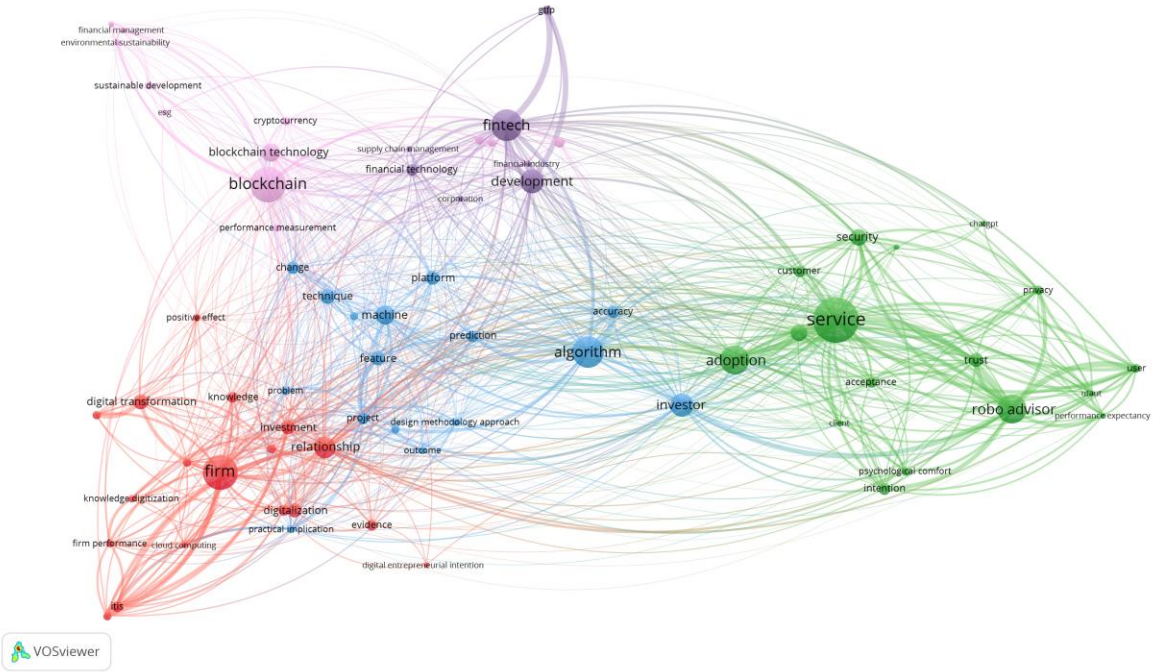

Fig.8.Keyword Density Map – FinTech Sector
Source: VOS viewer analysis based on 2018–2025 literature (n=150). Key themes include digitalization, algorithms, blockchain, and robo advisory services.

Furthermore, the visibility of terms such as "security," "privacy," "trust," and "psychological comfort" indicates an active discourse on addressing consumer trust, emphasizing the ethical implications and the need for robust, secure AI implementations. Finally, the emergence of sustainability-oriented keywords, including "sustainable development," "ESG," and

"environmental sustainability," signals a growing scholarly and practical interest in utilizing AI to align FinTech innovations with broader environmental, social, and governance objectives, thus demonstrating a holistic and ethically grounded approach to technological advancement in financial services.

Productivity Metrics: The word cloud derived from NVIVO's thematic analysis of productivity metrics within the FinTech sector highlights critical concepts central to productivity enhancement. The analysis includes the 100 most frequent words considering our coded framework under the productivity metrics section in the NVIVO package. Figure 9 presents a couple of prominent keywords such as "digital," "financial," "technology," "banks," and "advisors," underscore the sector's emphasis on digital transformation, particularly through the deployment of financial technology solutions and automated advisory services like robo-advisors. The frequent appearance of terms like "clients," "services," and "investments" suggests that productivity in FinTech is increasingly tied to innovative service models that optimize client interactions, investment decision-making processes, and customer experiences. Additionally, keywords such as "data," "performing," and "risks" indicate the industry's strong reliance on data analytics, predictive modeling, and algorithm-driven decision-making like credit scoring assessment as critical productivity drivers. The consistent mention of "sustainable," "impact," and "human" reflects a growing recognition within the sector of the need to balance technological efficiency with sustainability, human-centric design, and positive societal outcomes. These themes collectively demonstrate FinTech's strategic alignment of productivity initiatives with economic performance and responsible innovation.

On the other hand, specific studies highlight the significant role of AI adoption in enhancing productivity metrics within the FinTech sector. For instance, AI-driven technologies considerably elevate bank productivity by closely aligning services with consumer preferences, reducing operational costs, and improving overall banking performance and workforce efficiency (Lee, Ni and Zhang, 2023). Moreover, the authors note that user adoption remains uneven, as trust and psychological comfort act as critical moderating factors. Labor investment efficiency is defined through the relationship between observed and expected net hiring, indicating how AI technologies may optimize workforce allocation by minimizing discrepancies between actual and anticipated labor needs (Sai Wang *et al.*, 2024). Furthermore, advanced financial technologies like big data analytics and cloud computing contribute to better risk identification and management, ensuring financial system stability and improved resource allocation efficiency (Huang *et al.*, 2024). Notably, incorporating environmental factors into productivity calculations, such as Green Total Factor Productivity (GTFP), demonstrates how FinTech development facilitates sustainable economic growth by addressing environmental protection and efficient resource utilization. GTFP considers resource utilization and environmental protection as well as the input constraints of traditional economic growth (Ye, Xu and Chen, 2023). Specifically, Total Factor Productivity only considers labour and capital as inputs and desirable outputs, eliminating the variables of resource inputs and undesired outputs (e.g. sewage, SO2, and solid

waste). To overcome the barriers of TFP, more scholars have incorporated resource inputs and environmental impacts into the TFP framework and proposed various models to measure GTFP (Ye, Xu and Chen, 2023). Moreover, Metrics including carbon emissions, renewable energy usage, blockchain technology adoption, and GDP per capita offer quantitative measures for assessing these impacts (Hu and Li, 2023; Ye, Xu and Chen, 2023). Collectively, these insights illustrate how integrating AI technologies in financial services not only boosts economic performance but also promotes environmental sustainability and more effective resource management.

Fig.9.Word Map- Productivity metrics- Fintech sector

Challenges: By generating word clouds such as the one in Figure 10, we highlight critical workforce and challenge-related themes associated with AI adoption in the FinTech sector. Key concepts emerging prominently include "technology," "financial models," "data," "risk," and "human," underscoring the integral role technology and data analytics play within financial services. Moreover, "risk," "security," and "privacy" emphasize ongoing concerns regarding data integrity, algorithmic transparency, and cybersecurity threats inherent to AI integration. The recurring presence of "human", "advisors", "digitizing", and "skills "suggests an evolving dynamic where human expertise remains crucial, even as digital solutions become dominant. Additional terms like "regulators," "ethical," "transparency", and "manipulation" reflect the sector's recognition of ethical considerations and regulatory frameworks as essential for sustainable AI deployment. Collectively, these themes indicate that successful AI adoption in FinTech hinges on effectively managing technological integration alongside workforce transformation and rigorous adherence to regulatory standards and ethical practices.

Fig.10.Word Map- Workforce and social challenges- Fintech sector

Taken together, several studies emphasize efficiency gains from AI in fraud detection, labor allocation, and risk management (Lee, Ni and Zhang, 2023; Huang *et al.*, 2024; Sai Wang *et al.*, 2024) , while other studies highlight persistent challenges. For instance, issues of consumer trust and psychological comfort remain central (Bawack, Wamba and Carillo, 2021), while regulatory uncertainty and the ethical use of customer data complicate large-scale adoption (Holzinger *et al.*, 2023). Furthermore, the integration of sustainability metrics such as Green Total Factor Productivity shows heterogeneous results, with some studies highlighting positive alignment with FinTech innovation (Hu and Li, 2023; Ye, Xu and Chen, 2023), but other studies question the consistency of these measures across regions. Consequently, these conflicting findings suggest that while AI offers measurable productivity benefits in FinTech, the actual implementation of these gains remains conditional on regulatory clarity, consumer confidence, and the robustness of measurement frameworks.

Retail Sector

Themes and Insights: The VOS viewer density map for the retail sector highlights key themes and insights related to artificial intelligence adoption and productivity. The density map deployed a text analysis by focusing on the tiles and abstracts of every paper in our final sample of the retail sector. Notably, "customer loyalty," "satisfaction," and "interaction" stand out prominently, underscoring the strategic emphasis retailers place on enhancing consumer relationships through AI-driven experiences. The significant presence of "adoption," "process," "machine learning", and "framework" indicates that AI implementation in retail is driven by structured approaches aimed at improving operational processes and aligning AI adoption with business objectives. Additionally, the frequent occurrence of "demand" and "product" emphasizes retailers' efforts to optimize inventory management and forecasting accuracy using AI-powered tools. Finally, the keywords "time," "seller," and "trust" reveal the industry's focus on streamlining consumer-seller interactions, building trustworthy relationships, and achieving greater efficiency and responsiveness in customer service. For instance, the study by Gleim et al.

(2025) highlighted that in the post-purchase stage, retailers may gain a competitive advantage by realizing how consumers value the unboxing experience, evaluate products, and deepen customer engagement and trust in this new shopping environment (Gleim *et al.*, 2025). Furthermore, the study by Singh et al. (2019) highlighted the importance of moving away from the industrial mindset to a more customer-centric mindset, which reveals the impact of technology in changing customer preferences. Thus, it is notable to mention how customer preferences evolve and drive innovation in smart technologies (Singh and Thirumoorthi, 2019). Consequently, all the insights collectively illustrate the strategic deployment of AI in retail, focusing simultaneously on operational effectiveness and deepening customer engagement.

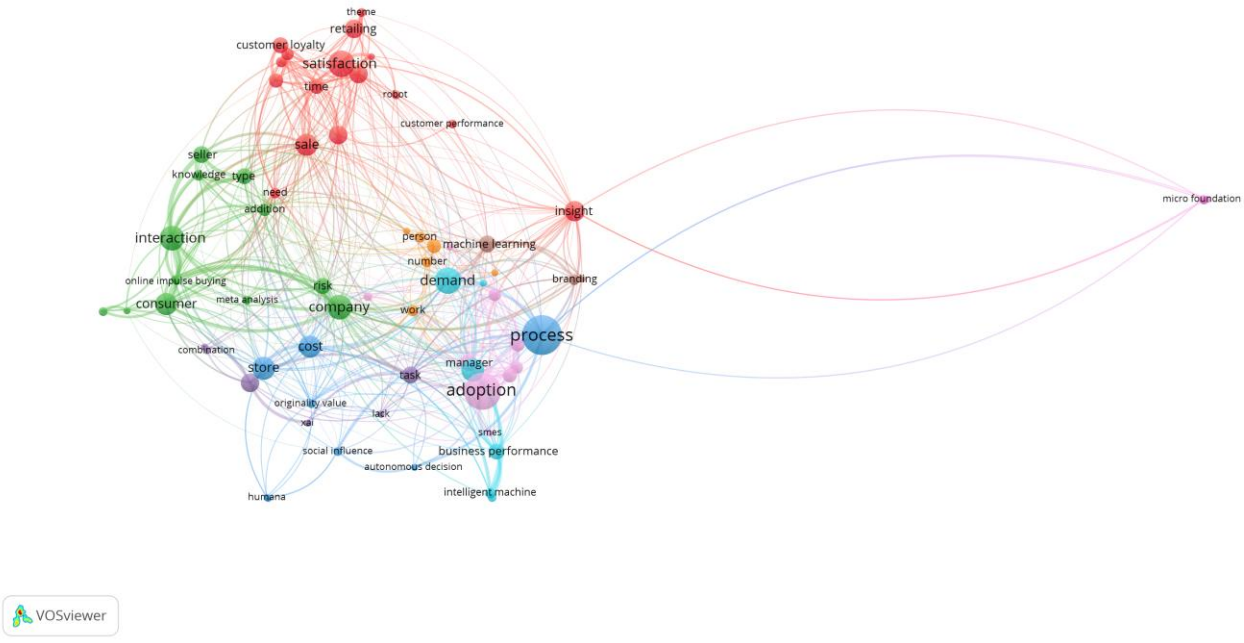

Fig.11.Themes Density Map- Retail Sector

Source: VOS viewer analysis based on 2018–2025 literature. Highlights include personalization, customer loyalty, generative AI for branding, and demand forecasting

Productivity Metrics: The word cloud derived from NVIVO's thematic analysis of productivity metrics within the Retail sector highlights critical concepts central to productivity enhancement. The analysis includes the 100 most frequent words considering our coded framework under the productivity metrics section in the NVIVO package. Figure 12 presents a couple of central keywords such as "customers," "services," "product," "retail," and "managers," which signify that retail productivity initiatives predominantly focus on enhancing customer experiences, optimizing service delivery, and refining product offerings. The prominence of terms like "performance," "systems," "operations," and "efficiency" further emphasizes the retail sector's

strategic use of AI to streamline operational processes, improve decision-making capabilities, and achieve higher resource utilization. Additionally, the occurrence of "cost," "impact," and "decisions" underscores AI's role in cost optimization and the tangible impacts on business outcomes. Collectively, these insights suggest that retail firms prioritize customer-centric performance metrics, operational effectiveness, and managerial decision-making as primary drivers of AI-enabled productivity enhancement.

On the other hand, specific studies highlight the significant role of AI adoption in enhancing productivity metrics within the Retail sector. Customer experience performance is frequently assessed using contextualized models that integrate consumer personality traits, trust, and privacy considerations (Goldberg, 1990), with empirical validation through surveys of retail consumers (Bawack, Wamba and Carillo, 2021). For instance, Bawack et al. (2021) highlighted how trust and privacy shaped consumer acceptance of AI adoption in the retail sector. Their findings support that personalization can enhance loyalty, but data use concerns can moderate adoption. Therefore, themes such as "time", "seller", and "trust" have emerged in the thematic analysis. Additionally, interactive multi-criteria decision-making frameworks, such as TODIM, have been applied to select optimal big data analytics tools. These frameworks use criteria including supply-chain flexibility, customer integration, and operational capacity (Gopal *et al.*, 2024). Moreover, AI implementation is measured by its efficiency in accelerating e-commerce processes, demonstrating a direct correlation between AI use, employee efficiency, resource allocation, and overall business performance (Fonseka, Jaharadak and Raman, 2022). Lastly, AI's effect on customer relationship management (CRM) performance is commonly evaluated through indicators such as relationship-building effectiveness, customer retention strategies, and decision-making simplification, underscoring the strategic importance of AI in enhancing customer loyalty and business growth (Li *et al.*, 2023; Paul Dhinakaran *et al.*, 2024).

Fig.12.Word Map- Productivity metrics- Retail sector

Challenges: By generating word clouds such as the two pictures in Figure 13, we highlight critical workforce and challenge-related themes associated with AI adoption in the Retail sector. In terms of workforce productivity, dominant keywords such as "productivity," "employees," "technology," and "human resources" highlight a significant emphasis on the optimization of labor through technological adoption, particularly AI-driven automation and analytics. The prominent presence of terms like "data," "impact," "job," and "intelligence" indicates a strong focus on leveraging AI for data-driven decision-making to enhance operational efficiencies and employee performance. On the other hand, challenge-related keywords, including "customer," "privacy," "ethical," "trust," and "risk," reveal growing concerns among retail firms regarding ethical decision-making, consumer trust, and data privacy in AI-powered interactions. Overall, these insights reflect the dual imperative faced by retail organizations: the need to enhance workforce productivity and efficiency through AI, balanced carefully with addressing consumer-related ethical concerns and risks associated with technological integration.

Fig.13.Word Map- Workforce and social challenges- Retail sector

Finally, more contradictory findings link AI adoption to improved personalization, operational optimization, and e-commerce efficiency (Shankar *et al.*, 2021b; Fonseka, Jaharadak and Raman, 2022; Yeh *et al.*, 2022; Li *et al.*, 2023). Although the evidence is scarce, past research demonstrates that consumer acceptance is highly contingent on trust and privacy considerations, with concerns that dependence on personal data may undermine long-term adoption (Bawack, Wamba and Carillo, 2021). On the other hand, some contributions emphasize AI's role in enhancing loyalty and growth (Paul Dhinakaran *et al.*, 2024), while several studies warn that ethical risks and consumer hesitation can offset short-term productivity benefits (Chauhan, Majumder and Kumar, 2023). This phase highlights a central paradox in retail: AI-driven tools can strengthen customer relationships but may simultaneously weaken them if consumer trust is not sustained as a competitive advantage.

Advanced Manufacturing Sector

Themes and Insights: The VOS viewer density map for the advanced manufacturing sector highlights key themes and insights related to artificial intelligence adoption and productivity. The density map deployed a text analysis by focusing on the titles and abstracts of every paper in our final sample of the advanced manufacturing sector. Central among these themes is the emphasis on energy efficiency and energy consumption, underscoring the sector's focus on sustainability and optimization of resource utilization. Closely related is the prominence of smart manufacturing, indicating an extensive adoption of digital technologies and AI-powered solutions to enhance production processes, decision-making, and operational performance. The frequent occurrence of terms such as digital technology, IoT, deep learning, and algorithms reinforces the significant role of advanced digital infrastructures and AI-driven analytical capabilities within the sector. Moreover, the keywords green innovation and sustainable development reflect industry-wide efforts towards integrating environmentally-friendly practices and achieving long-term ecological sustainability. Finally, the presence of terms like resilience and maturity model suggest a strategic approach within the manufacturing industry to withstand disruptions, enhance agility, and systematically evaluate technological advancement and adoption maturity.

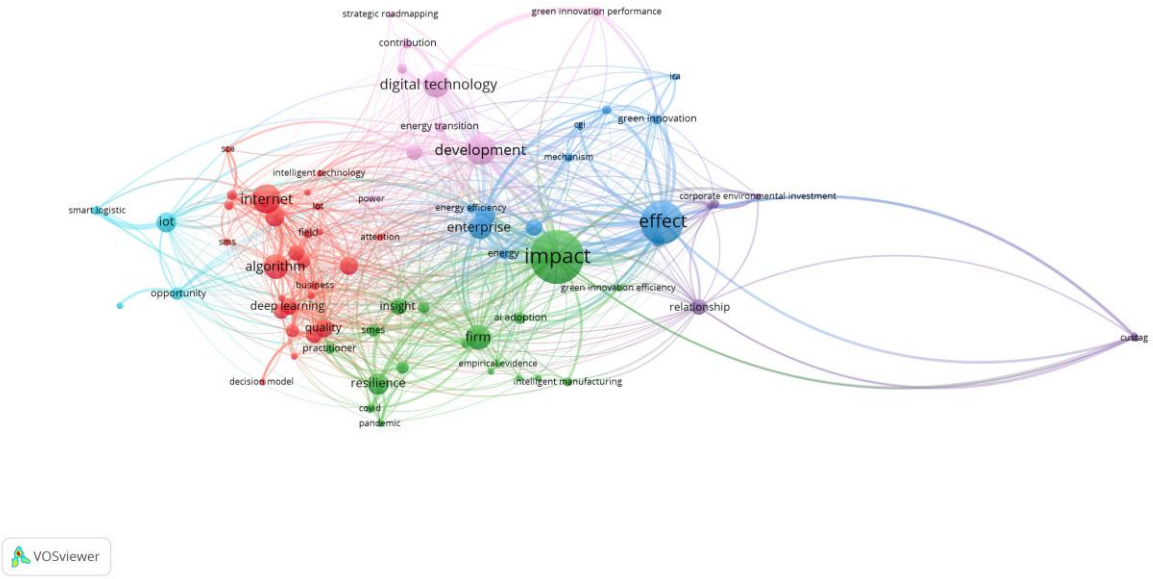

Fig.14.Themes Density Map- Advanced Manufacturing Sector

Source: VOS viewer analysis based on 2018–2025 literature. Central themes relate to predictive maintenance, smart manufacturing, process optimization, and energy efficiency.

Productivity Metrics: The word cloud derived from NVIVO's thematic analysis of productivity metrics within the Advanced Manufacturing sector highlights critical concepts central to productivity enhancement. The analysis includes the 100 most frequent words considering our coded framework under the productivity metrics section in the NVIVO package. Figure 15 presents the prominence of keywords such as "manufacturing", "data", "products", "technology", and "systems", underscoring the sector's emphasis on integrating intelligent technologies and data-driven systems into operational processes. "Energy consumption" and "sustainability" also emerge as significant themes, reflecting manufacturers' strategic orientation toward sustainable operations and efficient resource utilization. Further, the inclusion of terms such as "robots", "machining", and "automation" illustrates the industry's increasing reliance on automated solutions to enhance productivity and reduce operational costs. Concepts like "decisive", "predictive", and "innovativeness" indicate a focus on proactive, strategic decision-making and continuous innovation as critical productivity drivers. Collectively, these insights reflect an advanced manufacturing landscape actively engaging in technological integration and sustainability to optimize performance and maintain a competitive advantage.

On the other hand, specific studies highlight the significant role of AI adoption in enhancing productivity metrics within the Advanced Manufacturing sector. Studies leveraging organizational information processing theory identify that AI-driven cognitive insights, process automation, and cognitive engagement significantly enhance manufacturers' resilience and performance, especially planned resilience, directly influencing operational effectiveness (Yu *et al.*, 2024a). Additionally, research examining AI capabilities, digital transformation, and carbon neutrality underscores that digitally transformed firms exhibit greater competencies in achieving sustainability objectives and enhanced green supply chain performance (Rashid *et al.*, 2024; Shahzad *et al.*, 2024). Finally, empirical evidence demonstrates productivity spillovers linked to intelligent technologies, indicating that the increasing adoption of AI, flexible automation, additive manufacturing, and big data positively influences aggregate productivity, emphasizing a long-run equilibrium relationship between knowledge related to intelligent technologies and productivity outcomes (Venturini, 2022). Following the study by Venturini (2022), the example of Siemens' Industrial Copilot provides a practical case, as it enables engineering teams to generate automation code for PLCs more efficiently, thereby reducing downtime and supporting productivity gains in industrial operations. Thus, these findings collectively confirm the transformative role of AI in fostering productivity growth, resilience, and sustainability in advanced manufacturing contexts.

Fig.15.Word Map- Productivity metrics- Advanced Manufacturing sector

Challenges: By generating word clouds such as the respective two pictures in Figure 16, we highlight critical workforce and challenge-related themes associated with AI adoption in the Advanced Manufacturing sector. Key workforce themes highlighted include "industry," "technology," "productivity," "jobs," and "labor," suggesting that the adoption of advanced technologies, particularly AI and automation, significantly reshapes employment structures and skill requirements within the sector. The frequent appearance of terms such as "skills," "digitize," and "innovator" underscores the necessity of workforce adaptability, continuous skill enhancement, and innovation in response to technological disruptions. The challenges-related word map further emphasizes themes of "manufacturing," "systems," "energy," "environmental," and "sustainable," indicating critical concerns around integrating advanced technologies sustainably into existing production systems, minimizing environmental impacts, and managing resource consumption effectively. Collectively, these visual analyses reflect an initiative for the sector to strategically balance technological advancement with workforce development and sustainable management practices.

Fig.16.Word Map- Workforce and social challenges- Advanced Manufacturing sector

To conclude that section, studies in the advanced manufacturing literature frequently identify productivity improvements through automation, predictive maintenance, and digital transformation (Rashid *et al.*, 2024; Shahzad *et al.*, 2024; Yu *et al.*, 2024b). On the other hand, contrasting evidence suggests that skill mismatches, integration costs, and workforce displacement risks remain substantial barriers for productivity gains (Ballestar *et al.*, 2021; Hearn *et al.*, 2023; El Bhilat, El Jaouhari and Hamidi, 2024). Although research confirms productivity spillovers from intelligent technologies, indicating long-run equilibrium benefits (Venturini, 2022), a few studies stress that such gains are unevenly distributed and contingent on firm capabilities and resource allocation. This mixed evidence suggests that AI adoption in manufacturing is transformative but not universally effective, with actual outcomes depending on firm readiness, workforce adaptability, and sustainability strategies.

3.4 OECD- Inputs and Outputs Framework

FinTech Sector

Framing the findings through the OECD AI systems framework, AI adoption in FinTech leverages vast volumes of customer data, financial transaction logs, and behavioral analytics (Inputs). These feed into core AI systems such as fraud detection, credit scoring, customer segmentation, and personalized financial advice (AI Tasks). The successful implementation depends on enablers like strong cybersecurity infrastructure, algorithm transparency, trust-building mechanisms, and regulatory compliance, particularly under financial regulation regimes (Enablers). Together, these dynamics result in measurable gains in operational efficiency, improved customer experience, enhanced risk management, and long-term productivity improvements across financial service providers (Outputs).

Retail Sector

Applying the framework, retail firms rely on consumer behavior data, real-time inventory data, and e-commerce interaction logs as inputs to support machine learning models for personalization, demand forecasting, and supply chain optimization (Inputs). Core AI tasks include classification, prediction (e.g., demand), and recommendation (e.g., chatbot engines), enhancing marketing and operational strategies (AI Tasks). Next, complementary enablers include workforce upskilling, clear data governance, and consumer trust, especially around data privacy and explainability of AI decisions (Enablers). The resulting outcomes include cost reductions, operational efficiency, dynamic pricing, and enhanced customer engagement, all contributing to sector-specific productivity gains (Outputs).

Advanced Manufacturing Sector

In line with our suggested framework, AI adoption in advanced manufacturing is driven by inputs such as real-time sensor data, industrial IoT systems, and advanced analytics infrastructure

(Inputs). AI systems are deployed for process automation, predictive maintenance, anomaly detection, and smart quality control (AI Tasks). Therefore, key enablers include skilled personnel, system integration readiness, and innovation culture, complemented by strategic alignment with green manufacturing goals and digital twin adoption (Enablers). The tangible outputs include reduced downtime, improved energy efficiency, cost optimization, and enhanced operational resilience, which represent key levers of productivity growth in this sector (Outputs).

3.5 Industry financial reports

Fintech Sector

Analysis of 10-K reports from key fintech companies highlights extensive AI adoption aimed at strengthening fraud prevention, enhancing operational efficiency, and boosting productivity. The main goal of this approach was to systematically identify the definitions, the improvements, and the measurements of each company considering AI adoption and productivity actions. For instance, Visa employs advanced AI-driven solutions, such as Visa Deep Authorization and Visa Risk Manager, effectively reducing transaction fraud and improving consumer protection. The company has invested significantly—approximately $3 billion over a decade—to enhance network efficiency and facilitate secure global transactions. PayPal's strategic deployment of AI prioritizes enhanced customer interactions and robust fraud detection; it launched new AI-powered tools like PayPal Complete Payments, Venmo Commerce, and Cash Back rewards to optimize consumer experiences. In addition, Monzo leverages AI to streamline internal operations and manage fraud risk, achieving measurable improvements in customer acquisition, team productivity, and financial results, indicated by metrics such as average revenue per user (ARPU). Finally, Square integrates AI to accelerate seller growth through automation in marketing, inventory management, and operations, thereby driving greater revenue optimization.

Retail Sector

To continue with the next sector, top retail firms such as Amazon, Walmart, Shopify, Costco, and Home Depot significantly incorporate AI technologies to enhance customer experience, optimize supply chain operations, and improve overall productivity. First, Amazon utilizes AI extensively in supply chain optimization and personalized customer experiences, including delivery improvements through regionalization and advanced cost-efficiency via AWS's AI-enabled "Graviton chips." AI-driven advertising tools further amplify user engagement and revenue growth. Second, Walmart applies AI for efficient inventory management, same-day delivery optimization, and customer behaviour analytics, achieving substantial reductions in waste and supply chain emissions under its Project Gigaton initiative. Moreover, the example of Shopify harnesses AI-powered tools like Shop Pay and Shopify Magic, streamlining inventory management and supporting global merchant expansion. Similarly, Costco employs AI strategically in supply chain logistics, refining inventory management and pricing strategies to

maintain competitiveness. Finally, Home Depot enhances customer experiences by deploying AI-driven computer vision and machine learning technologies, such as the "Sidekick" tool, to optimize in-store navigation and real-time stock management.

Advanced Manufacturing Sector

To conclude that section, leading firms in advanced manufacturing, including Boeing, GE, IBM, and Siemens, extensively integrate AI technologies to optimize productivity, improve product quality, and enhance system reliability. Boeing leverages AI-driven predictive maintenance and simulation technologies, substantially reducing production cycle times and enhancing product quality, as evidenced by efficiency improvements in its 737 MAX and 787 production lines. The business initiative of GE that employs AI for turbine optimization and predictive maintenance significantly boosts productivity and system reliability within its energy sector operations. On the other hand, IBM utilizes its advanced AI data platform (Watsonx), enabling predictive analytics and automation of industrial processes, enhancing operational efficiencies across production lines and IoT integrations. Finally, Siemens incorporates AI extensively through digital twin technologies and automation tools, significantly reducing production errors, optimizing energy consumption, and improving resource allocation by constructing a smart infrastructure to expand the use of IoT technologies to optimize their daily activities. Notably, the AI-powered assistant, named Siemens Industrial Copilot, connected to the Totally Integrated Automation (TIA) Portal, further supports engineering teams in generating complex automation codes efficiently for programmable logic controllers (PLCs) to find the right help topic faster. That was one of the first generative AI products for engineering in an industrial environment. For instance, the TIA Portal can use the code suggestion from the AI, avoiding the need to copy and paste. Next, there is one capability for the Siemens Industrial Copilot to explain code blocks or to guide and create an initial machine or plant visualisation in integrated software and future proof web technology. In addition, engineering teams can search the manuals of Siemens in natural language, and customers will have the option to access their private instance of Azure OpenAI Service. Therefore, Siemens industrial copilot is enriched with the large language models of Microsoft Azure OpenAI Service which does not use customer data to retrain models.

4. POLICY RECOMMENDATIONS

The policy recommendations are informed by the UK's evolving AI governance landscape, emphasizing innovation-friendly regulation and strategic national investment. The UK Government's AI Regulation White Paper (2023) established five cross-sector principles—safety, transparency, fairness, accountability, and contestability—enabling a decentralized, sector-led approach rather than a single overarching AI Act. Building on this, the AI Opportunities Action Plan (January 2025) outlines targeted actions under three pillars: laying

strong AI foundations, embracing AI to improve lives, and securing long-term leadership in AI. The recommendations below are designed to align with these principles while supporting responsible AI deployment and productivity growth across FinTech, Retail, and Advanced Manufacturing. For instance, in the advanced manufacturing sector, the continuous emphasis on "green manufacturing" and "workforce upskilling" highlights a role for public policy in supporting sector-specific digital training programs and green co-investment schemes for AI deployment. In the retail sector, frequent references to "trust," "transparency," and "data ethics" point to the need for updated legal frameworks for explainable AI and consumer data protection. Finally, the fintech sector highlighted the need for "regulatory uncertainty," suggesting that agile policy instruments, such as regulatory sandboxes and cross-jurisdictional standards, can enable innovation while preserving transparency and implementation. These recommendations echo OECD priorities, particularly the link between technological adoption, institutional design, and workforce reskilling as drivers of productivity.

To ensure responsible and inclusive AI adoption across FinTech, Retail, and Advanced Manufacturing, targeted policy recommendations are essential to achieve this milestone. The following priorities should guide both public and private stakeholders:

Fintech Sector

As we highlighted previously in the results section, AI adoption in the FinTech sector enhances fraud detection, credit scoring, and algorithmic efficiency. Yet the findings also show that regulatory uncertainty and a lack of consumer trust constrain the full capabilities of productivity gains. Policymakers should prioritize adaptive regulatory framework that support the safe implementation of AI tools, such as predictive analytics in FinTech, to combat fraud and enhance transparency. This approach supports the UK's commitment to secure and trustworthy AI applications, such as regulatory sandboxes that were implemented in 2019 , that balance innovation, and knowledge diffusion with consumer protection. Therefore, it is notable to support the development and adoption of AI solutions by companies like Visa and PayPal, while promoting regulatory standards for data protection to sustain consumer trust, as demonstrated by Square and Monzo. This aligns with the UK's goal to enhance AI capabilities while safeguarding data privacy. Moreover, clear guidelines on algorithmic transparency and explainability in robo-advisors and automated decision-making systems would address adoption barriers while safeguarding trust. Greater international coordination of financial regulation could also reduce compliance costs for firms operating across borders .

Retail Sector

Considering the retail sector, our results highlighted that AI-driven personalization and logistics optimization support efficiency and customer engagement. However, concerns about data use and privacy remain major obstacles. To address these issues, policymakers should reinforce and

update data protection legislation to match the evolving capabilities of AI systems. Establishing ethical AI certification schemes for retail applications would help firms demonstrate responsible use of consumer data. Public information campaigns could further strengthen consumer confidence by clarifying how data is collected, processed, and protected. The promotion of explainable AI models can support the improvements in compliance and public trust. Furthermore, supporting retailers in implementing technologies such as Shopify's dynamic inventory management and Home Depot's AI-based in-store navigation, ensuring fair competition and ethical AI practices. These measures would enable retail firms to continue leveraging AI's efficiency potential without eroding long-term trust and align UK's emphasis on sector-specific AI adoption to boost productivity.

Advanced Manufacturing Sector

In the advanced manufacturing sector, the results from our systematic literature review consistently link AI adoption to productivity improvements through predictive maintenance, automation, and digital twin technologies. Simultaneously, skill shortages and capital requirements limit the breadth of adoption, particularly for small and medium-sized enterprises (SMEs). Policymakers could focus on workforce development through targeted vocational and reskilling programs, ensuring a bridge to close skill gaps. Therefore, businesses and employees remain competitive in an AI-driven economy. This supports one of the UK's objectives to build a robust AI talent pipeline. Finally, governments could also provide financial incentives or subsidies to encourage SMEs to adopt digital twin technologies and low-carbon AI applications. Therefore, policymakers need to focus on enhancing capabilities in areas like predictive maintenance, digital twins, and intelligent automation, as utilized by companies like Boeing, GE, IBM, and Siemens. This strategy supports the UK's ambition to lead in advanced AI applications, promotes productivity growth, and aligns with sustainability objectives.

5. CONCLUSION

This study sheds light on the initial investigation of the impact of AI adoption on firm-level productivity, with varying outcomes across the FinTech, Retail, and Advanced Manufacturing sectors. A database of more than 150 papers across various domains was used for the sectorial synthesis and analysis, serving as our primary information source. A sectorial synthesis of the literature covering the years 2018 to 2025 was conducted using the analysis tools of VOS Viewer and NVIVO for bibliometric insights and qualitative literature to ensure in-depth knowledge and hands-on analysis. Thus, our findings highlight different aspects and themes of AI adoption and productivity across industries, offering industry-specific benefits and challenges.

Considering the FinTech sector, AI enhances fraud detection and credit risk assessment by implementing AI and machine learning algorithms, though regulatory compliance and trust concerns hinder adoption. Moreover, the emerging themes of Blockchain which is central to digital banking by offering secure and transparent solutions. Furthermore, adopting services such as robo advisors depends on overcoming the challenges of trust and psychological comfort.

Secondly, the retail sector benefits from AI-driven marketing, demand forecasting, logistics optimization, cost reduction, and risk management, yet data privacy and consumer security remain barriers. Specifically, the variables of customer loyalty and operational efficiency seem to be the most emerging themes across the literature, while generative AI emerges as a tool for personalization and branding. However, the factors of trust, security, human capabilities, and job skills seem to underscore the importance of building customer confidence in AI-powered recommendations or services to enhance the human-AI collaboration effort but also to future-proof the workforce skills.

In the advanced manufacturing sector, AI enables predictive maintenance, smart manufacturing, energy optimization, and real-time monitoring, improving cost efficiency and process optimization, leading to better financial performance. However, workforce adaptability, system integration, and flexibility slow its AI adoption efforts, though a strategic road mapping and digital twins offer solutions for stakeholders and policymakers.

While cross-sector productivity gains from AI are evident, ranging from dynamic pricing, supply chain optimization, predictive maintenance, personalized banking, to quality control, measuring AI's true contribution remains difficult. There is a need for an appropriate discourse around valid quantitative measures and data acquisition because both robotics and big data analytics represent relevant elements of AI; they are neither entirely based on AI technology nor account for the entire scope of AI that is used in firms.

Future research should explore longitudinal impact assessments of AI adoption on comparative AI adoption models across multiple geographies and economic environments, as well as the role of AI in sustainable digital transitions and net-zero carbon initiatives, to measure green total factor productivity as a necessary variable of interest. Given that technological adoption of AI evolves over time and that consequences would be better captured in a processual way over the upcoming years, a dynamic perspective is needed; therefore, we call for more longitudinal studies, either quantitative or qualitative. Furthermore, following prior studies, it is crucial to estimate with appropriate quantitative variables whether AI has significantly impacted performance at the microeconomic level and identify which firms have benefited most to date (Zolas *et al.*, 2021; Korinek Anton, 2023). By advancing the discourse on AI and productivity, this study contributes valuable insights that can guide policymakers, industry leaders, and researchers in shaping the future of AI-driven economic transformation.

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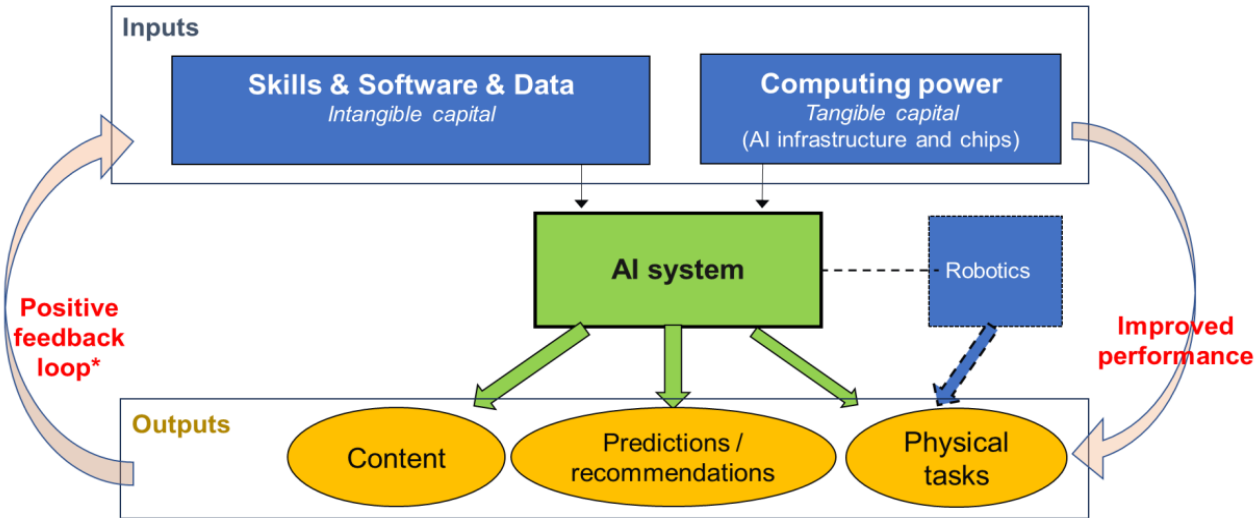
A. Appendix

Figure A1. AI Systems in a Production Function OECD (2024), "The Impact of Artificial Intelligence on Productivity, Distribution and Growth", Figure 1, p.9.



Note: This framework conceptualizes AI systems as combining intangible inputs—skills, software, and data—with tangible infrastructure such as computing power and chips to generate predictive, creative, or automated outcomes. The outputs—content generation, predictions, or physical task execution—are often intermediated through firm processes and capabilities.
It supports the analysis in this paper by framing how different types of AI adoption used by firms (e.g., analytics, personalization engines, recommender systems) can explain and discuss the main economic features and implications of AI systems. These categories align with the framework's emphasis on the interaction between technological components and business inputs in shaping productivity outcomes. This conceptual lens helps us interpret firm-level technology data and guide sectoral comparisons in FinTech, Retail, and Advanced Manufacturing.

Figure A2. Sector-Specific Keyword Search Strings Used in Scopus Database.

This appendix outlines the exact keyword search syntax used across the three sectors (FinTech, Retail, Advanced Manufacturing) during the data collection phase. These queries were run in Scopus and designed to target published journal articles from 2018 to 2025 that intersect artificial intelligence, productivity, and sector-specific terminology. Filters were applied to limit results by document type (journal articles), language (English only), and subject areas (Business, Economics, Decision Sciences, and Social Sciences). These searches provided 433 papers for

Fintech, 365 for Retail and 695 for Advanced Manufacturing, highlighting the foundation of the bibliometric and thematic analysis presented in this paper.

B. Appendix

Figure B1. FinTech Sector-Productivity Metrics- Top 30 Keywords

Word	Length	Count	Weighted Percentage (%)	Similar Words
data	4	93	1.32	data
technology	10	66	0.94	technologic, technological, technologies, technology, technology’
financial	9	60	0.85	financial, financially
human	5	54	0.77	human, humanity, humans
risk	4	50	0.71	risk, risks
models	6	48	0.68	model, modeling, modelling, models
services	8	44	0.62	service, services
potential	9	42	0.60	potential, potentialities, potentially
systems	7	42	0.60	system, systemic, systems
banks	5	38	0.54	bank, banking, banks
customer	8	34	0.48	customer, customers, customers', customers’, customization
esg	3	34	0.48	esg
fintech	7	33	0.47	fintech
advisors	8	32	0.45	advisor, advisors
business	8	31	0.44	business, businesses
market	6	31	0.44	market, marketing, markets, markets’
learning	8	30	0.43	learn, learning, learning’
robo	4	30	0.43	robo
security	8	30	0.43	secure, security
financial	8	30	0.43	financial
regulators	10	29	0.41	regulate, regulated, regulation, regulations, regulators
trust	5	29	0.41	trust, trusted, trusting
decision	8	27	0.38	decision, decisions
machine	7	27	0.38	machine, machines
processes	9	27	0.38	process, processes, processing
sustainability	14	26	0.37	sustainability, sustainable, sustainably
development	11	26	0.37	develop, developed, developers, developing, development
algorithms	10	25	0.35	algorithm, algorithmic, algorithms

concerns	8	25	0.35	concern, concerned, concerns
ethical	7	25	0.35	ethical, ethics

Figure B2. FinTech Sector-Workforce- Top 30 Keywords

Word	Length	Count	Weighted Percentage (%)	Similar Words
technology	10	1678	0.93	technological, technologically, technologies, technologies', technologies'', technology
digitizing	10	1204	0.67	digit, digital, digitalization, digitally, digitization, digitize, digitized, digitizing
data	6	1172	0.65	data, data'', data'and
industry	10	1028	0.57	industrial, industrialization, industrializing, industries, industry, industry''
products	8	850	0.47	product, production, production'', productive, productivity, products
economics	9	812	0.45	econom, economic, economically, economics
accounting	10	786	0.44	account, accountability, accountable, accountancy, accountant, accountants, accountants', accounted, accounting, accounts
effect	6	786	0.44	effect, effective, effectively, effectiveness, effects
robots	7	770	0.43	robot, robotic, robotics, robotization, robots, robots'
innovativeness	14	748	0.41	innov, innovate, innovating, innovation, innovations, innovative, innovativeness, innovator, innovators
impact	6	746	0.41	impact, impacted, impacting, impacts
managing	8	726	0.40	manag, manage, managed, management, manager, managers, managers', managing
develops	8	726	0.40	develop, developed, developer, developers, developing, development, development#, developments, develops
humans	6	672	0.37	human, humanities, humanizing, humans
intelligence	12	662	0.37	intelligence, intelligence'', intelligent, intelligent'',

				intelligently
green	5	630	0.35	green
skills	6	618	0.34	skill, skill’problem, skilled, skilling, skills
businesses	10	574	0.32	busi, business, businesses
financial	9	562	0.31	financial, financially
changing	8	504	0.28	chang, change, changed, changes, changing
applications	12	494	0.27	applicability, applicable, applicant, applicants, applicants’, application, applications, applications’’
growth	6	492	0.27	growth
countries	9	464	0.26	countries, countries’, country
occupations	11	440	0.24	occupation, occupational, occupations
efficiency	9	434	0.24	efficiencies, efficiency
entrepreneurship	16	434	0.24	entrepreneurship
investments	11	404	0.22	invest, invested, investing, investment, investments
advances	8	396	0.22	advance, advanced, advancement, advancements, advances, advancing
increase	8	396	0.22	increase, increased, increases, increasing, increasingly
informed	8	394	0.22	inform, informal, information, informative, informed, informing, informs
transforms	10	394	0.22	transform, transformation, transformational, transformations, transformative, transformed, transforming, transforms
employment	10	390	0.22	employ, employability, employed, employer, employers, employers’, employing, employment, employs

Figure B3. FinTech Sector-Challenges- Top 30 Keywords

Word	Length	Count	Weighted Percentage (%)	Similar Words
data	4	83	1.35	data
technology	10	59	0.96	technologic, technological, technologies, technology, technology’
financial	9	51	0.83	financial, financially
models	6	47	0.76	model, modeling, modelling, models
risk	4	45	0.73	risk, risks
systems	7	38	0.62	system, systemic, systems
banks	5	35	0.57	bank, banking, banks
potential	9	35	0.57	potential, potentialities, potentially
services	8	35	0.57	service, services
esg	3	34	0.55	esg
fintech	7	32	0.52	fintech
customer	8	31	0.50	customer, customers, customers', customers’, customization
human	5	29	0.47	human, humans
regulators	10	29	0.47	regulate, regulated, regulation, regulations, regulators
advisors	8	29	0.47	advisor, advisors
learning	8	29	0.47	learn, learning, learning’
security	8	28	0.45	secure, security
market	6	28	0.45	market, marketing, markets, markets’
business	8	27	0.44	business, businesses
financial	8	27	0.44	financial
machine	7	26	0.42	machine, machines
sustainability	14	26	0.42	sustainability, sustainable, sustainably
trust	5	26	0.42	trust, trusted
decision	8	25	0.41	decision, decisions
economic	8	25	0.41	economic, economically, economics
processes	9	25	0.41	process, processes, processing
robo	4	25	0.41	robo
ethical	7	24	0.39	ethical, ethics
privacy	7	24	0.39	privacy, privacy’

algorithms	10	23	0.37	algorithm, algorithmic, algorithms

Figure B4. Retail Productivity Metrics- Top 30 Keywords

Word	Length	Count	Weighted Percentage (%)	Similar Words
customs	7	465	2.22	custom, customer, customers, customers', customers', customization, customized, customs
performs	8	195	0.93	perform, performance, performances, performed, performing, performs
product	7	166	0.79	product, production, productivity, productized, products
managers	8	166	0.79	manage, managed, management, managers, managers', managing
services	8	160	0.77	service, serviceability, services
retail	6	144	0.69	retail, retailer, retailers, retailers', retailing, retails
model	5	127	0.61	model, modeling, modelling, models
technology	10	123	0.59	technological, technologies, technology
systems	7	123	0.59	system, systems
process	7	118	0.56	process, processes, processing
data	4	114	0.55	data
effect	6	114	0.55	effect, effective, effectively, effectiveness, effects
improve	7	107	0.51	improve, improved, improvement, improvements, improves, improving
online	6	102	0.49	online
impact	6	98	0.47	impact, impacts
business	8	96	0.46	business, businesses, busy
cost	4	95	0.45	cost, costly, costs
commerce	8	82	0.39	commerce
sellers	7	82	0.39	seller, sellers, sellers'
decisions	9	79	0.38	decision, decisions
operations	10	79	0.38	operates, operating, operation, operational, operationally, operations, operativity
efficient	9	78	0.37	efficiencies, efficiency, efficient, efficiently
capabilities	12	77	0.37	capabilities, capability, capable
consumers	9	77	0.37	consumer, consumers, consumers', consuming
quality	7	77	0.37	quality

shops	5	76	0.36	shop, shopping, shops
satisfaction	12	75	0.36	satisfaction
purchase	8	74	0.35	purchase, purchased, purchases, purchasing
intelligence	12	74	0.35	intelligence, intelligent
social	6	74	0.35	social
strategy	8	73	0.35	strategies, strategy
factors	7	72	0.34	factor, factored, factors
store	5	72	0.34	store, stores, storing
interactive	11	71	0.34	interact, interacting, interaction, interactions, interactive

Figure B5. Retail Sector-Challenges- Top 30 Keywords

Word	Length	Count	Weighted Percentage (%)	Similar Words
customer	8	194	2.49	customer, customers, customers', customization, customized
data	4	139	1.79	data
technology	10	90	1.16	technological, technologies, technology
retail	6	74	0.95	retail, retailer, retailers, retailers', retailing
services	8	66	0.85	service, services
adoption	8	56	0.72	adopt, adopted, adopting, adoption
trust	5	51	0.66	trust
consumer	8	50	0.64	consumer, consumers, consumers', consuming
humans	6	46	0.59	human, humanizing, humans
decisions	9	45	0.58	decision, decisions
interactions	12	44	0.57	interact, interacting, interaction, interactions, interactive
privacy	7	43	0.55	privacy
process	7	41	0.53	process, processes, processing
development	11	40	0.51	develop, developed, developers, developing, development
managers'	9	40	0.51	manage, management, managers, managers', managing
response	8	39	0.50	response, responses, responsibility, responsible, responsive
different	9	37	0.48	difference, differences, different
ethical	7	37	0.48	ethical, ethics
risks	5	37	0.48	risk, risks
systems	7	37	0.48	system, systems
marketing	9	36	0.46	market, marketers, marketing, markets
increasingly	12	35	0.45	increase, increased, increases, increasing, increasingly
user	4	35	0.45	user, users, users'
concerns	8	35	0.45	concern, concerned, concerns
personalized	12	33	0.42	person, personal, personalities, personality, personalization, personalized

smart	5	32	0.41	smart
impact	6	32	0.41	impact, impactful, impacts
shops	5	30	0.39	shop, shopping, shops
effectively	11	29	0.37	effect, effective, effectively, effects
understanding	13	29	0.37	understand, understanding
social	6	28	0.36	social
brand	5	27	0.35	brand, brands
content	7	27	0.35	content
voice	5	27	0.35	voice

Figure B6. Retail Sector-Workforce- Top 30 Keywords

Word	Length	Count	Weighted Percentage (%)	Similar Words
productivity	12	1936	0.97	product, production, productive, productivity, products
data	4	1706	0.86	data
human	5	1565	0.79	human, humanity, humans, humans'
technology	10	1547	0.78	technological, technologically, technologies, technology
employees	9	1386	0.70	employee, employees, employees', employees’
labor	5	1307	0.66	labor
resources	9	1164	0.59	resource, resources
study	5	1124	0.57	studied, studies, study, studying
intelligence	12	1118	0.56	intelligence, intelligences, intelligent, intelligibly
model	5	1032	0.52	model, modeled, modeling, modelled, models
employment	10	1030	0.52	employ, employability, employed, employers, employing, employment, employs
industry	8	1026	0.52	industrial, industrialization, industries, industries', industry
working	7	969	0.49	work, worked, working
service	7	953	0.48	service, services
marketing	9	940	0.47	market, marketers, marketing, markets
impact	6	912	0.46	impact, impacted, impacting, impacts
job	3	896	0.45	job, jobs
effect	6	887	0.45	effect, effective, effectively, effectiveness, effects
performance	11	870	0.44	perform, performance, performed, performing
tasks	5	839	0.42	task, tasks
systems	7	823	0.41	system, systems
research	8	815	0.41	research, researcher, researchers, researches
artificial	10	804	0.40	artificial, artificially
managing	8	793	0.40	manag, manage, managed, management, manager, managers, managing
customer	8	779	0.39	customer, customers, customers’

development	11	779	0.39	develop, developed, developer, developing, development, developments
algorithms	10	775	0.39	algorithm, algorithmic, algorithms, algorithms'
skills	6	773	0.39	skill, skilled, skills
generative	10	755	0.38	generate, generated, generates, generating, generation, generations, generative
innovation	10	741	0.37	innovation, innovations, innovative, innovativeness
analysis	8	734	0.37	analysis
significantly	13	732	0.37	significance, significant, significantly
robot	5	720	0.36	robot, robotic, robotics, robotization, robots
level	5	702	0.35	level, levels
process	7	700	0.35	process, processed, processes, processing

Figure B7. Advanced Manufacturing Sector-Productivity metrics- Top 30 Keywords

Word	Length	Count	Weighted Percentage (%)	Similar Words
products’	9	665	1.78	product, production, production’’, productive, productivity, products, products’
technology	10	511	1.37	technological, technologically, technologies, technologies’, technology
manufacturing	13	507	1.36	manufactur, manufacture, manufactured, manufacturer, manufacturers, manufacturing, manufacturing’
energy	6	358	0.96	energy
systems	7	334	0.89	system, systemic, systems, systems’
data	4	325	0.87	data
processing	10	278	0.74	process, processed, processes, processing
performance	11	250	0.67	perform, performance, performances, performed, performing, performs
improve	7	249	0.67	improve, improved, improvement, improvements, improves, improving
robots	6	236	0.63	robot, robotic, robotics, robotization, robots
innovativeness	14	225	0.60	innov, innovation, innovational, innovations, innovative, innovativeness
intelligent	11	220	0.59	intelligence, intelligent, intelligently
sustainable	11	203	0.54	sustain, sustainability, sustainable, sustainably, sustaining
developments	12	188	0.50	develop, developed, developers, developing, development, developments
digital	7	186	0.50	digit, digital, digitalization, digitally, digitization, digitized
operators	9	179	0.48	operate, operates, operating, operation, operational, operations, operator, operators
green	5	172	0.46	green
efficiently	11	165	0.44	efficiencies, efficiency, efficient, efficiently
reduce	6	158	0.42	reduce, reduced, reduces, reducing
resources	9	148	0.40	resource, resources
increase	8	147	0.39	increase, increased, increases, increasing, increasingly

impact	6	146	0.39	impact, impacted, impacting, impacts
machining	9	145	0.39	machine, machines, machining
managers	8	144	0.39	manage, managed, management, manager, managers, manages, managing
companies	9	142	0.38	companies, companies', companies’, company
adoption	8	139	0.37	adopt, adopted, adopting, adoption, adopts
environmental	13	136	0.36	environmental, environmentally
consumption	11	133	0.36	consumption
applications	12	128	0.34	applicability, applicable, application, applications
measuring	9	125	0.33	measurable, measure, measured, measurement, measurements, measures, measuring
optimizing	10	116	0.31	optimal, optimalization, optimism, optimization, optimize, optimized, optimizes, optimizing
costs	5	116	0.31	cost, cost’, costly, costs
smart	5	114	0.31	smart
quality	7	109	0.29	quality

Figure B8. Advanced Manufacturing Sector-Challenges- Top 30 Keywords

Word	Length	Count	Weighted Percentage (%)	Similar Words
technology	10	257	1.77	technological, technologically, technologies, technology
data	4	180	1.24	data
manufacturing	13	166	1.15	manufacturer, manufacturers, manufacturing
products	8	123	0.85	product, production, productive, productivity, products, products’
systems	7	116	0.80	system, systemic, systems, systems’
development	11	113	0.78	develop, developed, developers, developing, development, developments
processes	9	105	0.72	process, processes, processing
digitalization	14	105	0.72	digital, digitalization, digitally, digitization, digitized
adoption	8	82	0.57	adopt, adopted, adopting, adoption
managers	8	82	0.57	manage, management, manager, managers, managers', managing
performance	11	78	0.54	perform, performance, performances, performed, performing, performs
improve	7	75	0.52	improve, improved, improvement, improves, improving
implementation	14	74	0.51	implement, implementation, implementations, implemented, implementing
sustainable	11	73	0.50	sustain, sustainability, sustainable, sustainably
energy	6	68	0.47	energy
innovative	10	66	0.46	innov, innovation, innovations, innovative, innovativeness
environmental	13	63	0.43	environmental, environmentally
increase	8	63	0.43	increase, increased, increases, increasing, increasingly
smart	5	60	0.41	smart
applications	12	58	0.40	application, applications
governments	11	58	0.40	governance, governing, government, governments
organizations	13	58	0.40	organization, organizations, organizations’, organize, organized

green	5	56	0.39	green
skills	6	54	0.37	skill, skilled, skillfully, skills
impact	6	51	0.35	impact, impacted, impacting, impacts
security	8	50	0.35	secure, secured, security
human	5	49	0.34	human, humans
reduce	6	48	0.33	reduce, reduced, reduces, reducing
employees	9	48	0.33	employee, employees, employees', employees’
companies	9	47	0.32	companies, companies’, company
costs	5	46	0.32	cost, cost’, costly, costs
issues	6	45	0.31	issue, issues
enterprises	11	42	0.29	enterprise, enterprises, enterprises’
informed	8	42	0.29	informants, information, informational, informed

Figure B9. Advanced Manufacturing Sector-Workforce- Top 30 Keywords

Word	Length	Count	Weighted Percentage (%)	Similar Words
technology	10	9188	1.81	technological, technologically, technologies, technologies', technology, technology', technology'ssake
industry	8	7740	1.53	'industry, industrial, industrialism, industrialization, industrialized, industries, industries', industry
productivity	12	7725	1.52	product, production, productive, productivity, products
jobs	4	5142	1.01	job, jobs, jobs'
employs	7	4916	0.97	employ, employability, employed, employer, employers, employers', employing, employment, employs
laborers	8	4741	0.93	labor, labor', laborers
skills'	7	4704	0.93	skill, skilled, skilled', skills, skills'
development	11	3906	0.77	develop, developed, developers, developing, development, developments, develops
workers'	8	3760	0.74	worker, worker', workers, workers'
innovator	9	3681	0.73	innovate, innovating, innovation, innovation', innovations, innovative, innovatively, innovator, innovators
humans'	7	3512	0.69	human, humanity, humanized, humans, humans'
intelligent	11	3505	0.69	intelligence, intelligence', intelligent
labour	6	3487	0.69	labour, labour', labourers, labourers'
increase	8	3396	0.67	increase, increased, increases, increasing, increasingly
market	6	3330	0.66	market, marketing, marketization, markets, markets'
effect	6	3190	0.63	effect, effective, effectively, effectiveness, effects
robots'	7	3118	0.61	robot, robotic, robotics, robotization, robotization', robots, robots'
enterprises'	12	3084	0.61	enterprise, enterprises, enterprises'
digitize	8	2889	0.57	digit, digital, digitalization, digitization, digitize
manufacturing	13	2831	0.56	manufacture, manufactured, manufacturer, manufacturers, manufacturing
workings	8	2766	0.55	work, worked, working, workings, works
impact	6	2756	0.54	impact, impacted, impacting, impacts

automation	10	2588	0.51	automate, automated, automates, automating, automation
improve	7	2523	0.50	improve, improved, improvement, improvements, improves, improving
machines	8	2317	0.46	machine, machines
firms’	6	2277	0.45	firm, firmly, firms, firms’
highly	6	2267	0.45	high, highly
data	4	2249	0.44	’data, data
efficiently	11	2051	0.40	efficiencies, efficiency, efficient, efficiently
risk	4	1986	0.39	risk, risks
significantly	13	1964	0.39	significance, significances, significant, significantly
demand	6	1963	0.39	demand, demanded, demanding, demands
tasks	5	1774	0.35	task, tasks