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Assessing the Impact of Artificial Intelligence Tools on Employee Productivity: Insights from a Comprehensive Survey Analysis

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Abstract: This study provides a nuanced understanding of AI's impact on productivity and employment using machine learning models and Bayesian Network Analysis. Data from 233 employees across various industries were analyzed using logistic regression, Random Forest, and XGBoost, with 5-fold cross-validation. The findings reveal that high levels of AI tool usage and integration within organizational workflows significantly enhance productivity, particularly among younger employees. A significant interaction between AI tools usage and integration ($\beta = 0.4319$, $p < 0.001$) further emphasizes the importance of comprehensive AI adoption. Bayesian Network Analysis highlights complex interdependencies between AI usage, innovation, and employee characteristics. This study confirms that strategic AI integration, along with targeted training programs and ethical frameworks, is essential for maximizing AI's economic potential.

Keywords: Artificial Intelligence (AI); employee productivity; AI integration; machine learning models; Bayesian Network Analysis

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1. Introduction

Artificial Intelligence (AI) is emerging as a pivotal technology with the potential to revolutionize productivity and reshape the employment landscape across various economic sectors. Since the commercial release of advanced models like ChatGPT in late 2022, there has been heightened anticipation of a transformative shift comparable to the advent of the internet. However, this optimism is tempered by the reality of persistently low productivity growth in many advanced economies, which raises critical questions about the actual economic impact of AI and the mechanisms through which it influences productivity and employment [1].

AI's economic impact is multifaceted and complex. Theoretically, AI can be seen both as a complement and a substitute for human labor. When viewed as a complement, AI enhances human productivity by augmenting decision-making processes and operational efficiency [2]. Conversely, when viewed as a substitute, AI can automate tasks traditionally performed by humans, potentially leading to job displacement but also contributing to productivity gains [3,4]. Empirical evidence supports both perspectives, with studies indicating that AI-using firms often experience positive productivity effects without necessarily observing significant negative impacts on overall employment [5].

The challenge of measuring AI's economic impact is compounded by its intangible nature and rapid technological evolution. Traditional economic metrics and national accounting frameworks struggle to capture the full value generated by AI, often leading to an underestimation of its contributions [6]. This measurement difficulty contributes to what is known as the productivity paradox—where the rapid advancements in technology do not immediately translate into observable productivity gains [7]. Recent advancements in AI have explored the integration of machine learning models to better understand user sentiment and predict outcomes in various domains [8].

To tackle these challenges, this study aims to address these challenges by leveraging advanced machine learning models and Bayesian Network Analysis to analyze firm-level data and provide a more nuanced understanding of AI's impact on productivity and employment. Specifically, the research employs Random Forest and Gradient Boosting Machine (GBM) models to identify key predictors of productivity changes and assess their relative importance. By designing the questionnaire to gather granular data on AI tools usage, integration, and organizational factors, we address the issue of AI's intangibility by converting it into measurable constructs, such as AI_Integration_Level and AI_Tools_Complexity". Additionally, Bayesian Network Analysis is used to explore the probabilistic dependencies between various features, offering a comprehensive view of the dynamics at play. The Bayesian Network was constructed using the HillClimbSearch algorithm with Bayesian Information Criterion (BIC) to determine the optimal structure, balancing model complexity, and goodness-of-fit. Parameters were estimated via Maximum Likelihood Estimation (MLE), ensuring accurate representation of conditional probability distributions. Inference was conducted using Variable Elimination, a method suitable for capturing the intricate dependencies in the data. The performance of the models was rigorously evaluated using 5-fold cross-validation to mitigate overfitting and ensure robust performance metrics.

The research hypotheses are grounded in existing literature and empirical findings. First, it is hypothesized that AI integration significantly enhances productivity at the firm level, with AI integration being the most critical predictor of productivity change (Hypothesis 1). This is supported by studies showing substantial productivity gains in firms adopting AI technologies [9]. Second, it is hypothesized that the impact of AI on employment is complex, with positive productivity effects at the firm level not necessarily translating into negative employment effects at the aggregate level (Hypothesis 2). This hypothesis is informed by research indicating that AI can complement human labor, leading to new job creation and task augmentation rather than straightforward job displacement [3,4]. Third, it is hypothesized that the benefits of AI integration are moderated by factors such as AI complexity, areas of AI utilization, and employee characteristics (Hypothesis 3). This is supported by evidence that the impact of AI varies significantly across different contexts and applications [1,5].

By employing sophisticated analytical techniques and building on a robust theoretical foundation, this study seeks to contribute to the ongoing discourse on AI's economic impact. The findings will provide valuable insights for policymakers and business leaders, helping them to harness AI's potential for economic growth while mitigating potential adverse effects on employment. Through detailed feature importance analysis and the exploration of probabilistic dependencies, this research aims to offer a comprehensive understanding of AI's role in shaping the future of work and productivity.

The key contributions of this paper are multifaceted. First, it utilizes a unique dataset derived from a survey of 233 employees across various industries, providing valuable empirical insights into the ways AI tools impact productivity. The study goes beyond simplistic measures by considering the complexity of AI integration and its interaction with demographic factors such as age. Second, the research applies a diverse range of analytical techniques, including logistic regression with interaction terms, Random Forest, XGBoost, and Bayesian Network Analysis. This multi-method approach allows for a more nuanced and robust exploration of how AI influences employee productivity.

Third, the findings highlight the critical role of AI integration into organizational workflows, showing that merely adopting AI tools is insufficient without strategic and comprehensive integration. Moreover, this study uncovers generational differences in adaptability to AI tools, with younger employees experiencing greater productivity gains compared to their older counterparts. These generational insights suggest that adaptability to AI technologies may vary significantly across age groups. Finally, the paper offers practical recommendations for policymakers and business leaders, advocating for targeted training programs and the establishment of ethical frameworks to maximize AI's economic potential.

The remainder of this paper is structured as follows: Section 2 reviews the existing literature on AI's impact on productivity, focusing on both theoretical perspectives and empirical studies. Section 3 outlines the research methodology, including data collection, preprocessing, and the machine learning models employed in the analysis. Section 4 presents the findings, highlighting the results of the logistic regression, Random Forest, XGBoost, and Bayesian Network Analysis. Section 5 discusses the broader implications of these findings, particularly concerning AI's potential to enhance productivity and its differential effects across employee demographics. Finally, Section 6 concludes with recommendations for future research and strategies to optimize AI's role in the workplace.

2. Literature Review

AI holds significant promise for enhancing economic growth and efficiency, but its actual outcomes depend on various factors, including industry context, regulatory frameworks, and the complementary nature of human labor. The literature on AI's economic impacts is extensive, reflecting diverse perspectives on how AI technologies influence productivity, employment, and overall economic growth. This section provides an overview of the key perspectives and empirical findings regarding AI's influence on productivity, highlighting gaps that this study aims to address.

2.1. Theoretical Perspectives on AI's Economic Impact

AI is increasingly seen as a general-purpose technology capable of fundamentally transforming industries and economies [2]. From a theoretical perspective, AI and big data are not ideologically neutral. They serve as tools within the capitalist framework, reshaping labor, value, and production relations. Walton and Nayak (2021) [10] argue that AI exacerbates labor precarity while redefining traditional Marxist concepts of bourgeoisie and proletariat in an information-driven society [5,10]. This shift necessitates a reevaluation of established economic theories, particularly regarding labor value and production relations in the context of AI and big data-driven economies [6].

Furthermore, the potential for AI to enhance productivity through automation and decision-making optimization [3] contrasts with concerns about its impact on labor displacement and inequality [4]. Liu et al. (2024) [11] highlight AI's dual role in the workplace, where its usage can boost employee technological self-efficacy but also trigger workplace anxiety [5,11]. This highlights the need for a more nuanced understanding of AI's implications for labor and productivity.

AI can also automate tasks traditionally performed by humans, potentially leading to job displacement but contributing to productivity gains [3,12].

Cornelli et al. [13] examined AI-related investments across 86 countries, reporting a shift from mid-skill to high-skill and managerial positions, a decline in the labor share of income, higher total factor productivity (TFP), and increasing inequality. Baily, Brynjolfsson et al. [7] argue that AI could increase aggregate productivity by 33% over 20 years through its impact on knowledge workers' productivity. Korinek [14] considered the transition to Artificial General Intelligence (AGI), highlighting its potential to automate a wide range of tasks and its complex effects on wages.

Empirical Evidence and Productivity Gains

Empirical studies provide mixed results on AI's economic impacts. Comunale and Manera [15] found that AI's productivity gains are not uniformly distributed across industries. For example, a PricewaterhouseCoopers (PwC) report predicted that AI could increase global GDP by $15.7 trillion between 2018 and 2030, with varying regional impacts [16].

Eisfeldt et al. [17] constructed a firm-level measure of workforce exposure to AI in the US and studied the impact of ChatGPT's release on equity returns. Rammer et al. [18] found that AI increased the probability of German firms introducing new products or processes by about 8%. Babina et al. [19] reported significant increases in patents and trademarks associated with AI but no increase in sales per worker. Conversely, ref. [20] estimated a 6.8% increase in sales per worker for firms innovating in AI technologies, while [5] put this number at 4.4%.

2.2. Measurement Challenges and the Productivity Paradox

Rapid technological advancements do not immediately translate into observable productivity gains, a paradox highlighted by [7]. Parteka and Kordalska (2023) [21] present evidence of a productivity paradox where, despite advances in AI technology, measurable gains in macroeconomic productivity remain limited [8,21]. This phenomenon is often attributed to the slow diffusion of AI technologies and the time lag between adoption and tangible productivity benefits [10].

Regulatory approaches must align with AI technologies to maximize benefits and mitigate adverse effects [13].

2.3. The Need for Task-Level and Sector-Level Productivity Data

To truly understand how AI impacts productivity and jobs in different sectors, we need specific data at both the task level (what exact tasks AI replaces or enhances) and the industry level (whether the company is in manufacturing, healthcare, etc.). These details are critical for analyzing how AI affects employment and productivity in different contexts. AI exacerbates inequalities within the labor market, disproportionately affecting low-skilled workers while benefiting those with advanced technical skills [10]. Hunt et al. (2021) [22] report that AI is more likely to be associated with both job creation and destruction, with the overall net effect dependent on organizational strategies and industry contexts [18,22]. This highlights the importance of organizational policies and managerial strategies in shaping the outcomes of AI integration.

Precise productivity estimates are important for analyzing employment effects. Research on text-generating AI's productivity impact is silent on image generation, despite its significant labor market effects [23]. Bridging the gap between theoretical predictions and empirical findings requires addressing measurement challenges and aligning AI adoption with human capabilities [1].

Practical examples of AI's effect on productivity are seen in customer service and professional tasks. For instance, chatbots (AI-powered tools) in customer service allow support agents to handle more inquiries. Chatbots have enhanced productivity in customer service, with AI-assisted support agents handling 13.8% more inquiries per hour [24]. Automation tools like robotic process automation (RPA) significantly improve operational efficiency, enabling business professionals to produce 59% more documents per hour and programmers to code 126% more projects per week [20,21].

2.4. Measuring beyond Output

Xie and Yan (2024) [25] found that AI enhances the agglomeration of productive services in industries such as manufacturing and IT by boosting productivity [24]. However, their study also reveals regional differences in AI's effects, with more dynamic and innovative industries reaping greater benefits. This aligns with previous research that suggests AI's productivity impact is contingent on industry-specific factors such as capital intensity, technological infrastructure, and innovation ecosystems [25].

Moreover, Khanna and Sharma (2024) [26] highlight the network spillovers associated with AI investments, particularly in industries with high levels of digital infrastructure. Their findings suggest that firms in these sectors are better positioned to capitalize on AI technologies, leading to superior productivity gains compared to those in more traditional industries.

Traditional productivity metrics, such as lines of code per day, fail to capture downstream costs like technical debt and overlook essential elements of software development [27,28]. Holistic metrics that focus on end-to-end outcomes, project completion times, and comprehensive development pipeline views are essential [27,28].

2.5. Measuring AI's Business Impact

Tangible business outcomes like user adoption, revenue, and customer satisfaction should be prioritized. Predicting development bottlenecks, automating routine tasks for more predictable release cycles, enhancing code reliability, and reducing bugs are important for improving software quality and customer satisfaction [29].

While AI's theoretical models predict transformative impacts, empirical findings are mixed and vary across industries and contexts. Addressing measurement challenges and aligning AI adoption with complementary human capabilities is essential for realizing AI's full economic potential.

In conclusion, the literature indicates that AI's potential for improving productivity is evident, but its realization depends on several contextual factors, including industry, regulation, and labor dynamics. This study aims to build on these insights by addressing the gaps related to how AI integration, usage complexity, and employee characteristics influence productivity across various organizational contexts.

3. Materials and Methods

In our study, we employed an anonymous survey to gather data from participants. Given that our survey was conducted anonymously, obtaining formal informed consent was not necessary. However, ethical guidelines were strictly adhered to by informing participants about the nature and purpose of our research prior to their participation. Participants were clearly notified that their responses would remain anonymous, ensuring that individual privacy and confidentiality were preserved throughout the study.

The dataset utilized in this study was derived from a survey in which we applied a questionnaire administered to employees across various industries. To ensure the validity and reliability of the data collected, several measures were implemented:

1. Questionnaire Design: The questionnaire was meticulously designed to cover a broad spectrum of variables related to employee demographics, AI tool usage, productivity changes, and organizational factors. Each question was crafted to align with the research objectives, ensuring content validity. The goal was to capture a comprehensive set of factors that influence the relationship between AI usage and employee productivity, while also addressing organizational factors like AI-related training, ethical considerations, and company culture. Table 1 presents a summary of the questions included in the questionnaire and in our analysis, along with the response options. The questionnaire covered a wide range of variables, including employee demographics, job characteristics, organizational attributes, and AI usage patterns. This breadth ensured that the survey could capture not only the technical aspects of AI usage (e.g., integration level and complexity of AI tools) but also the contextual factors like job creation, organizational structure changes, and ethical considerations. The questionnaire was specifically structured to capture how AI technologies impact employee productivity and organizational workflows. AI tools usage and integration levels were measured through specific questions to convert these abstract concepts into measurable constructs. These AI-related questions provided the foundation for analyzing how AI adoption influences productivity, job creation, and changes in organizational structure. By focusing on factors such as AI training, ethical implications, and job opportunities, the survey ensured that the complex, intangible benefits of AI could be rigorously analyzed using machine learning models and Bayesian Network Analysis. The inclusion of AI-related factors supports the study's aim to explore generational differences in AI adaptability and provides a framework for evaluating how AI technologies contribute to overall business innovation and competitiveness.
2. Pilot Testing: Prior to full-scale deployment, the questionnaire underwent pilot testing with a smaller subset of the target population. Feedback from the pilot test was used

to refine the questions, improve clarity, and eliminate ambiguities, thereby enhancing face validity.

3. Reliability Assessment: Polychoric alpha, an extension of Cronbach's alpha, was used for evaluating the internal consistency of scales composed of ordinal data. This approach was particularly useful when dealing with mixed data types, including ordinal, categorical, and numeric variables.
4. Data Preprocessing: The dataset columns were renamed for clarity and consistency, and categorical data were cleaned to ensure uniformity. Ordinal columns were encoded to numerical values based on predefined mappings, and gender was binary encoded to numerical values. Categorical variables such as Residence, Industry, and Position were transformed into dummy variables to handle categorical data in the analysis. Boolean columns were converted to numeric values, ensuring all data were in a suitable format for analysis. Numeric variables, specifically 'AI_Integration_Level' and 'AI_Tools_Complexity', were standardized using the StandardScaler to ensure comparability.
5. Feature Engineering: Each question was crafted to ensure that it directly related to the research questions and hypotheses. For example, questions on AI usage and its frequency were tied to measuring the degree of AI integration and its impact on productivity. By doing this, the questionnaire was able to translate complex, intangible concepts (like AI integration or innovation impact) into measurable constructs that could be statistically analyzed. Important questions, identified as relevant to the study, were combined with the numeric variables for analysis. These important questions included: AI Tools Usage, Years Using AI, Job Opportunities Creation, Org Structure Changes, Partnerships Experience, Innovation and Competitiveness Improvement, Communication and Collaboration Changes, Company Culture Engagement, Ethical Considerations, Ethical Policies Implementation, Future Preparedness, AI Training Provided, and Customer Satisfaction Changes.
6. Interaction terms and polynomial features for the numerical variables were created to capture potential non-linear effects.
7. A function was defined to calculate the polychoric alpha, involving factor analysis to determine the communalities (h2), calculating the average variance extracted (AVE), and finally computing the polychoric alpha using the formula:

$$\alpha_{poly} = \frac{N \times AVE}{1 + (N-1) \times AVE} \tag{1}$$

where N is the number of items. The polychoric alpha for the combined set of important questions and numeric variables ('AI_Tools_Usage', 'Years_Using_AI', 'Job_Opportunities_Creation', 'Org_Structure_Changes', 'Partnerships_Experience', 'Innovation_and_Competitiveness_Improvement', 'Communication_and_Collaboration _Changes', 'Company_Culture_Engagement', 'Ethical_Considerations', 'Ethical_Policies _Implementation', 'Future_Preparedness', 'AI_Training_Provided', 'Customer _Satisfaction_Changes') was calculated to be 0.84. This high value suggested a good level of internal consistency among the items.
8. Construct validity was assessed by examining the relationships between different variables in the dataset. Factor analysis (Table 2) was employed to identify underlying constructs and ensure that the questionnaire items accurately represent the theoretical constructs they were intended to measure. The results indicated a single-factor solution with substantial factor loadings, suggesting a coherent underlying construct. Construct validity was assessed by examining the relationships between different variables in the dataset through factor analysis, which confirmed the hypothesized factor structure with significant factor loadings. The questionnaire was shared through Prolific, ensuring a high response rate and engagement. We received 233 responses, which is adequate for this type of statistical analysis. This sample size provides a sufficient basis for reliable and valid statistical analysis, ensuring the generalizability

of the results. Additionally, there were no missing values (NaNs) in the responses, which further enhanced the robustness and reliability of the dataset. Efforts were made to achieve a diverse and representative sample by distributing the questionnaire across multiple industries and ensuring participation from various employee demographics, thus mitigating response bias and enhancing external validity.

9. Response Rate and Representativeness: The response rate to the questionnaire was carefully monitored to ensure representativeness. Efforts were made to achieve a diverse and representative sample by distributing the questionnaire across multiple industries and ensuring participation from various employee demographics. The sample size of 233 responses was deemed sufficient based on power analysis for logistic regression, which is a suitable method for classification problems. The required sample size for logistic regression can be calculated using the formula for minimum sample size estimation in logistic regression.

$$N = \frac{\left(Z_{\frac{\alpha}{2}} + Z_{\beta}\right)^2 \times p \times (1-p)}{(\log(OR))^2} \quad (2)$$

where

- $Z_{\frac{\alpha}{2}}$ is the Z-value for the desired level of confidence (e.g., 1.96 for 95% confidence).
- Z_{β} is the Z-value for the desired power (e.g., 0.84 for 80% power).
- p is the estimated proportion of the outcome.
- OR is the anticipated odds ratio.

Table 1. Questionnaire's items considered in this study.

Question Included in the Questionnaire	Variable	Option	Percentage
What is your age?	Age (1–6 scale, 6 for 41+)	18–20	2.58%
		21–25	22.75%
		26–30	22.75%
		31–35	21.03%
		36–40	12.02%
		41+	18.88%
Rate the level of AI integration in your daily operations on a scale of 1–10 (1 being minimal and 10 being extensive).	AI_Integration_level (scale 1–10)	scale	numeric
On a scale of 1–10, how would you rate the complexity of AI tools and systems used in your organization (1 being very simple and 10 being highly complex)?	AI_Complexity_level (scale 1–10)	scale	numeric
What is your highest level of education?	Education (1–4 scale, 4 for Doctorate)	High school	18.88%
		Undergraduate	20.60%
		Graduate	53.22%
		Doctorate	7.30%
You currently use artificial intelligence tools that support you in carrying out your daily work processes. These include, among others: Chat GPT, Google BARD, ChatSonic, Claude, Google LaMDA, Perplexity AI, Neuroflash, GitHub Copilot, or Jasper Chat.	AI_Tools_Usage (scale 1–4 scale, 4 for All the time)	Never	17.17%
		Occasionally	42.06%
		Often	31.76%
		All the time	9.01%

Table 1. *Cont.*

Question Included in the Questionnaire	Variable	Option	Percentage
What percentage increase in productivity has been observed since the implementation of AI?	Productivity_Change_Percentage (1–5 scale, 5 for 80–100%)	0–20%	46.78%
		20–40%	26.18%
		40–60%	18.45%
		60–80%	7.73%
		80–100%	0.86%
For how many years have you been with the company?	Years_with_Company (1–4 scale, 4 for longer than 10 years)	0–2 years	39.91%
		2–4 years	22.32%
		4–10 years	23.61%
		longer than 10 years	14.16%
How long has your company been using AI or AI-based technologies?	Years_Using_AI (1–4 scale, 4 for more than 5 years)	less than a year	52.36%
		1–2 years	32.62%
		2–5 years	12.02%
		more than 5 years	3.00%
Has your organization provided any AI-related training or education programs for its employees?	AI_Training_Provided (0–2 scale, 2 for Yes)	No	63.95%
		currently in development	12.88%
		Yes	23.18%
To what extent do you agree with the following statement: "AI has created new job opportunities within our organization".	Job_Opportunities_Creation (1–5 scale, 5 for Strongly agree)	Strongly disagree	15.88%
		Disagree	28.76%
		Neither agree nor disagree	36.48%
		Agree	14.16%
		Strongly agree	4.72%
Has the implementation of AI led to any changes in the organizational structure or reporting lines in your company?	Org_Structure_Changes (0–2 scale, 2 for Yes)	No	72.53%
		unsure	23.18%
		Yes	4.29%
Has your organization experienced any collaborations or partnerships with other companies or industries as a result of AI adoption? (e.g., joint ventures and strategic partnerships)	Partnerships_Experience (0–2 scale, 2 for Yes)	No	66.95%
		unsure	27.47%
		Yes	5.58%
To what extent do you agree with the following statement: "AI has improved our organization's ability to innovate and stay competitive".	Innovation_and_Competitiveness _Improvement (1–5 scale, 5 for Strongly agree)	Strongly Disagree	5.15%
		Disagree	12.45%
		Neither agree nor disagree	38.20%
		Agree	36.91%
		Strongly agree	7.30%
Has the implementation of AI changed the nature of communication and collaboration within your organization?	Communication_and_ Collaboration_Changes (0–2 scale, 2 for Yes)	No	73.39%
		unsure	17.17%
		Yes	9.44%

Table 1. *Cont.*

Question Included in the Questionnaire	Variable	Option	Percentage
How has the adoption of AI affected the overall company culture and employee engagement within your organization?	Company_Culture_Engagement 0–4 scale, 4 for significant improvement)	No change	59.23%
		Slight improvement	33.48%
		Significant improvement	3.00%
		Slight decline	4.29%
To what extent has your organization considered the ethical implications of AI adoption, such as potential bias and transparency?	Ethical_Considerations (0–3 scale, 3 for extensively)	Not at all	23.61%
		Minimally	33.05%
		Moderately	33.91%
		Extensively	9.44%
Has your organization implemented any policies or guidelines to address the ethical implications of AI use?	Ethical_Policies_Implementation (0–2 scale, 2 for Yes)	No	63.09%
		Currently in development	19.31%
		Yes	17.60%
In your opinion, how well-prepared is your organization to adapt to future AI-driven changes in the workforce and the potential ripple effects?	Future_Preparedness (scale 1–5, 5 for Very well-prepared)	Very unprepared	9.44%
		Somewhat unprepared	23.18%
		Neutral	27.47%
		Somewhat prepared	31.33%
		Very well-prepared	8.58%
How has the implementation of AI affected customer satisfaction and relationships?	Customer_Satisfaction_Changes (1–5, 5 for Significant improvement)	Significant decline	0.00%
		Slight decline	2.15%
		No change	56.65%
		Slight improvement	34.76%
		Significant improvement	6.44%
What is your gender?	Gender (Male-1, Female-2. Prefer not to say-minus1)	Male	56.65%
		Female	42.49%
		Prefer not to say	0.86%
What is your current place of residence? (If you work in another place than you live, please fill in only the country in which you are currently employed)	Residence	Austria	0.86%
		Belgium	4.29%
		Canada	3.00%
		Croatia	0.43%
		Denmark	0.43%
		Finland	1.29%
		France	4.29%
		Freelancer	0.43%
		Germany	4.29%
		Greece	5.58%
		Hungary	4.29%
		Ireland	1.29%
		Italy	8.58%
		The Netherlands	2.15%

Table 1. *Cont.*

Question Included in the Questionnaire	Variable	Option	Percentage
What is your current place of residence? (If you work in another place than you live, please fill in only the country in which you are currently employed)	Residence	Poland	14.59%
		Portugal	18.45%
		Romania	16.74%
		Slovenia	1.72%
		Spain	2.15%
		Sweden	0.86%
		Switzerland	0.86%
		The Netherlands	0.86%
		United Kingdom	2.58%
In which industry does your company or the company you work in operate?	Industry	Arts and culture	0.43%
		Automotive	3.00%
		Banking	0.43%
		Chemical industry	0.86%
		Construction	4.29%
		Design and publicity	0.86%
		Education	11.16%
		Electrical industry	3.00%
		Energy sector	1.72%
		Environmental conservation	0.43%
		Film industry	0.43%
		Finance	2.58%
		Financial	0.86%
		Food and beverage	1.72%
		Game development	0.43%
		Gymnasium reception	0.43%
		Health service	6.44%
		Hospitality	0.43%
		Human resources	0.43%
		Insurance	0.43%
		Interior design_architecture _construction	0.43%
		IT industry	32.62%
		Legal	0.43%
		Logistics and supply chain	0.86%
		Management	0.43%
		Media and entertainment	0.86%
		Online publishing	0.43%

Table 1. *Cont.*

Question Included in the Questionnaire	Variable	Option	Percentage
In which industry does your company or the company you work in operate?	Industry	Pharmacy	0.43%
		Public service	6.87%
		Real estate	1.72%
		Retail	1.72%
		Sales	0.86%
		Service industry	9.44%
		Social	0.43%
		Supply chain	0.43%
		Telecommunications	0.43%
		Tourism	0.43%
		Transportation and distribution	0.86%
What position do you hold in this company?	Position	Lower or operative management	28.76%
		Manager	0.43%
		Middle management	0.86%
		Project management	0.86%
		Software engineer	0.43%
		Workforce	68.67%

Table 2. Factor loadings and communalities.

Item	Loading	Communality
AI_Tools_Usage (ordinal)	0.430	0.184
Years_Using_AI(ordinal)	0.474	0.224
Job_Opportunities_Creation (ordinal)	0.578	0.333
Org_Structure_Changes (ordinal)	0.220	0.048
Partnerships_Experience (ordinal)	0.299	0.089
Innovation_and_Competitiveness_Improvement (ordinal)	0.702	0.492
Communication_and_Collaboration_Changes (ordinal)	0.265	0.070
Company_Culture_Engagement (ordinal)	0.491	0.241
Ethical_Considerations (ordinal)	0.626	0.391
Ethical_Policies_Implementation (ordinal)	0.485	0.234
Future_Preparedness (ordinal)	0.533	0.284
AI_Training_Provided (ordinal)	0.492	0.242
Customer_Satisfaction_Changes (ordinal)	0.572	0.327
AI_Integration_Level (numerical)	0.598	0.358
AI_Tools_Complexity (numerical)	0.600	0.359

Assuming an anticipated proportion p of 0.5 (which maximizes the required sample size) and an odds ratio OR of 2, the calculation would yield a sample size requirement of approximately 168. The actual sample size of 233 responses provides a robust basis for analysis, ensuring reliable and generalizable results.

Data Collection and Preprocessing

The dataset comprised 233 responses from employees across various industries. The data were collected via a questionnaire distributed through Prolific, ensuring a high response rate and engagement.

1. Preprocessing Steps:
   - Ordinal Encoding: Categorical variables were encoded to ordinal scales.
   - Binary Encoding: Gender was encoded as 1 for Male, 0 for Female, and −1 for Prefer not to say.
   - Dummy Variables: Categorical variables such as Residence, Industry, and Position were transformed into dummy variables.
   - Scaling: Numerical columns were standardized using the StandardScaler.
   - Interaction Terms: Interaction terms between AI Tools Usage and AI Integration Level and AI Tools Usage and AI Tools Complexity were created.
2. Logistic Regression Model: The target variable, Productivity_Change_Percentage, was re-encoded into a binary outcome, Productivity_Change_Binary, defined as 1 for notable productivity change (≥40%) and 0 for lesser changes (<40%). Feature selection was performed using LassoCV, identifying significant predictors such as Age, Innovation, and Competitiveness Improvement, and interaction terms involving AI tools. A logistic regression model was fit using the selected features, and its performance was evaluated using classification metrics, including precision, recall, F1-score, and the ROC AUC score.
3. Random Forest and XGBoost Models were implemented to capture non-linear relationships and interactions between features. Hyperparameter tuning and 5-fold cross-validation were used to optimize model performance and ensure robustness.
4. Bayesian Network Modeling: A Bayesian Network was constructed using the HillClimbSearch algorithm and Bayesian Information Criterion (BIC) for structure learning. Maximum Likelihood Estimation (MLE) was used for parameter learning, and inference was performed using Variable Elimination.
5. Bayesian logistic regression with Markov Chain Monte Carlo (MCMC) sampling was also employed, with priors assumed to follow a normal distribution. Posterior predictive checks and 5-fold cross-validation were used to validate the model.

Analyses were conducted using Python 3.8 and key libraries such as Pandas for data manipulation, scikit-learn for machine learning models, PyMC and Arviz for Bayesian inference, and pgmpy for probabilistic graphical models. Correlations between variables were computed using the polycor library in RStudio.

The analyses were performed on Google Colab Pro with an NVIDIA A100 GPU and L4 GPU, leveraging 25 GB of RAM and high-speed cloud storage for efficient handling of large datasets and computationally intensive tasks.

4. Results

To understand the demographics, AI usage, and organizational impacts among respondents, a detailed questionnaire was administered. The detailed distribution of responses for each question (Table 1) helps in understanding the demographic and professional background of the respondents, as well as their experiences and perceptions related to AI implementation. Table 3 provides descriptive statistics for the numerical variables, offering insights into the central tendencies and variability within the dataset. The variable AI_Integration_Level refers to the extent to which AI tools are embedded into the organizational workflows. The variable AI_Tools_Complexity refers to the sophistication and functionality of the AI tools employed within the organization. The variables were measured on a continuous numerical scale, with higher values representing a more comprehensive and advanced integration of AI within the organization. These numerical summaries help contextualize the findings and validate the robustness of the subsequent analyses.

Table 3. Descriptive statistics for numerical variables.

Variable	Mean	Std	Min	25%	50%	75%	Max
AI_Integration_Level	4.090	2.587	1	2	4	6	10
AI_Tools_Complexity	3.773	2.341	1	2	3	6	9

4.1. Logistic Regression Model

To focus on the predictors of significant productivity changes, the target variable, 'Productivity_Change_Percentage', was re-encoded into a binary outcome, 'Productivity_Change_Binary'. This binary outcome was defined as 1 for notable productivity change ($\geq$40%) and 0 for lesser changes (<40%). This threshold was chosen to distinguish between minor and substantial productivity improvements, thus providing a clearer understanding of the factors contributing to significant productivity enhancements.

Feature selection was performed using LassoCV, a regularization technique, to identify significant predictors. LassoCV was chosen for its ability to handle multicollinearity and select the most relevant features, thereby improving the model's performance. Interaction terms were included to capture the combined effect of AI tools usage with integration levels and tool complexity. The LassoCV feature selection identified the following key predictors: Age, Innovation and Competitiveness Improvement, AI Tools Usage * AI Integration Level, and AI Tools Usage * AI Tools Complexity.

A logistic regression model was fit using the selected features (Table 4). The model's performance was evaluated using classification metrics, including precision, recall, F1-score, and the ROC AUC score.

Table 4. Logistic regression results for predicting productivity change (features selected with Lasso first).

Feature	Coefficient	Std. Error	z-Value	*p*-Value	(95% Confidence Interval)	Odds Ratio	Lower CI	Upper CI
Age	−0.4079	0.109	−3.752	0.000	−0.621 to −0.195	0.665051	0.537433	0.822973
AI Integration Level	1.2208	0.206	5.914	0.000	0.816 to 1.625	3.390040	2.261944	5.080749
Innovation and Competitiveness Improvement	0.0606	0.117	0.519	0.604	−0.168 to 0.289	1.062446	0.845212	1.335513
Model Summary								
Dependent Variable	Productivity_Change_Binary				Number of Observations		233	
Method	Maximum Likelihood Estimation (MLE)				Log-Likelihood		−100.98	
Pseudo-R-squared	0.2575				LLR *p*-value		6.222×10^{-16}	
Classification Metrics	Value							
Precision (Class 0)	0.83				Precision (Class 1)		0.65	
Recall (Class 0)	0.90				Recall (Class 1)		0.49	
F1-score (Class 0)	0.86				F1-score (Class 1)		0.56	
Accuracy	0.79				Macro avg F1-score		0.71	
Weighted avg F1-score	0.78				ROC AUC Score		0.835	
Confusion Matrix	**Predicted Negative**					**Predicted Positive**		
Actual Negative	153					17		
Actual Positive	32					31		

We also included interaction terms and fit the second logistic regression model. The interaction terms between AI Tools Usage and AI Integration Level and AI Tools Usage and AI Tools Complexity were included to explore potential multiplicative effects. The rationale was that the productivity impact of AI tools might not only depend on their usage or complexity alone but also on how these tools are integrated within the organization. High levels of integration can enhance the utility and effectiveness of AI tools, amplifying their impact on productivity.

Table 5 presents the logistic regression results with interaction terms, including the odds ratios for the significant predictors. The model showed a good fit with a pseudo-R-squared value of 0.2687 and a log-likelihood of −99.453. Notably, the interaction term between AI Tools Usage and AI Integration Level demonstrated a significant positive association (β = 0.4319, $p < 0.001$), indicating that increased usage and higher integration levels collectively enhance productivity.

Table 5. Logistic regression results for predicting productivity change (features selected with Lasso first and Interaction Terms).

Feature	Coefficient	Std. Error	z-Value	*p*-Value	(95% Confidence Interval)	Odds Ratio	Lower CI	Upper CI
Age	−0.4520	0.109	−4.161	0.000	−0.665 to −0.239	0.636346	0.514312	0.787336
Innovation and Competitiveness Improvement	0.0366	0.117	0.312	0.755	−0.193 to 0.266	1.037267	0.824525	1.304901
AI Tools Usage * AI Integration Level	0.4319	0.081	5.358	0.000	0.274 to 0.590	1.540144	1.315084	1.803720
Model Summary								
Dependent Variable	Productivity_Change_Binary			Number of Observations			233	
Method	Maximum Likelihood Estimation (MLE)			Log-Likelihood			−99.453	
Pseudo-R-squared	0.2687			LLR *p*-value			9.380×10^{-16}	
Classification Metrics	Value							
Precision (Class 0)	0.84			Precision (Class 1)			0.66	
Recall (Class 0)	0.90			Recall (Class 1)			0.52	
F1-score (Class 0)	0.87			F1-score (Class 1)			0.58	
Accuracy	0.80			Macro avg F1-score			0.73	
Weighted avg F1-score	0.79			ROC AUC Score			0.837	
Confusion Matrix	**Predicted Negative**						**Predicted Positive**	
Actual Negative	153						17	
Actual Positive	30						33	

Main findings

- Age: A negative coefficient (β = −0.4520, $p < 0.001$) suggests that older age groups are associated with lower productivity changes.
- AI Tools Usage * AI Integration Level: This interaction term had a positive coefficient (β = 0.4319, $p < 0.001$), indicating that the combined effect of frequent AI tool usage and high integration levels significantly increases the likelihood of productivity improvement.
- AI Tools Usage * AI Tools Complexity: Although this interaction term was positive (β = 0.0840), it was not statistically significant ($p = 0.264$).

- The inclusion of interaction terms revealed important insights into how AI tools usage, when combined with high integration levels, can substantially enhance productivity. This underscores the importance of not only adopting AI tools but also ensuring their comprehensive integration within organizational workflows. The model's (with interaction terms) overall accuracy was 80%, with a macro average F1-score of 0.73. The ROC AUC score of 0.837 indicates a strong discriminative ability of the model. However, the relatively lower recall for the positive class (0.52) suggests that further refinement is needed to improve the model's sensitivity.
- The model achieved an overall accuracy of 80%, with a ROC AUC score of 0.837, indicating good discriminative ability.

The findings suggest that age and the interaction between AI Tools Usage and AI Integration Level are significant predictors of notable productivity changes. Specifically, younger employees and those working in environments where AI tools are heavily used and well-integrated are more likely to experience significant productivity gains. These insights highlight the importance of targeted training and integration strategies to maximize the benefits of AI adoption.

Further, LassoCV and RidgeCV were employed to handle multicollinearity and select the most relevant features. The selected features by Lasso included Age, Innovation and Competitiveness Improvement, Communication and Collaboration Changes, AI Tools Usage * AI Integration Level, AI Tools Usage * AI Tools Complexity, and AI Tools Usage Squared. Ridge selected a more comprehensive set of features, including various demographic and organizational attributes. The final combined set of features from both Lasso and Ridge included Age, Innovation and Competitiveness Improvement, AI Tools Usage * AI Integration Level, AI Tools Usage * AI Tools Complexity, AI Tools Usage Squared, and several additional features from the Ridge selection.

The logistic regression model with interaction terms and polynomial features for the numerical variables, validated through 5-fold cross-validation, exhibits satisfactory performance with a 0.7512 ± 0.0369 accuracy and a 0.7692 ± 0.0409 ROC AUC score. The model is proficient in distinguishing between the two classes, though enhancements in predicting notable productivity changes are needed.

The complexity and variety of the dataset variables justify the use of advanced ensemble methods like Random Forest and XGBoost. Our dataset includes diverse features such as 'Age', 'Gender', 'Education', 'AI_Tools_Usage', 'AI_Integration_Level', two interaction terms, and two polynomial features. While logistic regression is useful for identifying key predictors and understanding direct relationships, it has limitations in capturing complex non-linear interactions and dependencies between variables.

The logistic regression analysis highlighted significant predictors like 'Age' and the interaction between 'AI Tools Usage' and 'AI Integration Level', but its linear nature restricts its ability to uncover more intricate patterns and relationships. While innovation remains a theoretically important factor in productivity gains, the specific dynamics captured in this study may be more closely tied to the direct influence of AI tools usage and integration.

To further improve predictive performance, we implemented Random Forests and XGBoost models, evaluated through cross-validation. Random Forests and other tree-based methods, like XGBoost, inherently capture interactions between features due to their hierarchical nature. This means they can handle interactions without explicitly requiring the interaction terms to be manually created. The interpretability techniques SHAP and LIME were employed to gain deeper insights into model predictions, providing transparency and understanding of feature contributions.

4.2. Random Forest and XGBoost

Random Forest and XGBoost are powerful ensemble learning methods that offer several advantages for our analysis:

- Handling Non-Linearity and Interactions: Both models can naturally capture non-linear relationships and interactions between variables without the need for explicit feature engineering. This is important given the interaction terms and polynomial features in our dataset, such as 'AI_Tools_Usage * AI_Integration_Level' and 'AI_Tools_Usage_Squared'.

- Feature Importance: Random Forest and XGBoost provide insights into feature importance, helping to identify which variables and interactions have the most significant impact on productivity changes. This aligns with our goal of understanding the key factors driving productivity.

The Random Forest model was configured with 200 estimators and a random state of 42. The choice of 200 estimators strikes a balance between computational efficiency and model performance, as increasing the number of trees typically enhances the model's robustness and generalization capabilities but also raises computational costs. The random state ensures reproducibility of the results. The best parameters that resulted from hypertuning were bootstrap = True, max_depth = None, min_samples_leaf = 2, min_samples_split = 2, and n_estimators = 200. This configuration was evaluated using 5-fold Stratified Cross-Validation (CV) to maintain class balance across folds, providing a reliable performance estimate and minimizing the risk of overfitting by ensuring the model is tested on all subsets of the data.

Similarly, the XGBoost model was configured with 100 estimators to maintain consistency with the Random Forest model and to leverage the strength of ensemble methods in boosting performance through multiple iterations. The use_label_encoder = False parameter was set to bypass the default label encoder in XGBoost, facilitating a direct use of the preprocessed labels and preventing potential encoding issues. The eval_metric = 'logloss' was chosen to align the evaluation with logistic regression settings, as log-loss provides a robust metric for binary classification problems by penalizing false classifications proportionally to their confidence. The best parameters resulted from hypertuning were 'colsample_bytree': 0.6, 'gamma': 0.1, 'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 100, and 'subsample': 0.6. This setup ensures that the model is optimized not just for accuracy but also for the confidence of predictions, enhancing its overall reliability and interpretability. The 5-fold Stratified Cross-Validation for the XGBoost model similarly ensures class balance and provides a comprehensive evaluation of the model's performance, reducing the likelihood of overfitting and ensuring generalizability across different subsets of the data.

The Random Forest classifier achieved a Cross-Validated ROC AUC of ROC AUC: 0.8114 ± 0.0627. This indicates that the model is relatively stable across different subsets of the data, with the average ROC AUC indicating good discriminatory ability, though the standard deviation suggests some variability.

The XGBoost classifier achieved a Cross-Validated ROC AUC of 0.8098 ± 0.0556. This indicates that the model performs well across different subsets of the data, with the average ROC AUC showing good discriminatory ability and a relatively low standard deviation indicating consistent performance.

Both Random Forest and XGBoost classifiers show moderate to good performance in predicting the binary productivity change outcome. The Random Forest model has a slightly higher accuracy and cross-validated ROC AUC score compared to the XGBoost model, indicating it might perform better on this dataset. However, both models exhibit some variability in performance, as indicated by the standard deviations of the cross-validated ROC AUC scores.

Both models effectively capture non-linear relationships and interactions between features (Figures 1 and 2). The high importance of interaction terms and polynomial features underscores this capability.

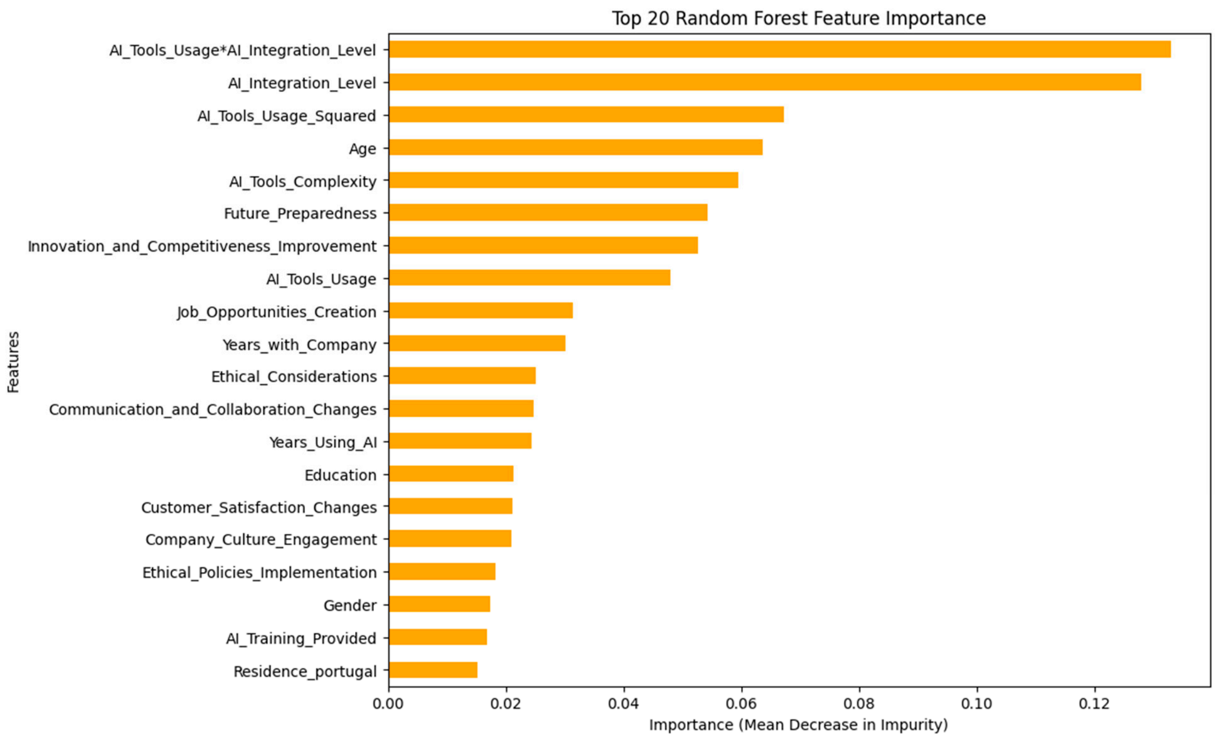

Figure 1. Top 20 Random Forest feature importance. AI_Tools_Usage * AI_Integration_Level (the combined influence of AI tools usage and integration level), AI_Integration_Level, and AI_Tools_Usage. The polynomial term AI_Tools_Usage_Squared indicates non-linear effects. Other Important Features: Strategic factors like Innovation_and_Competitiveness_Improvement and Future_Preparedness are significant. Residence_portugal and Job_Opportunities_Creation suggest that specific regions and workforce structure might have particular influences on productivity changes.

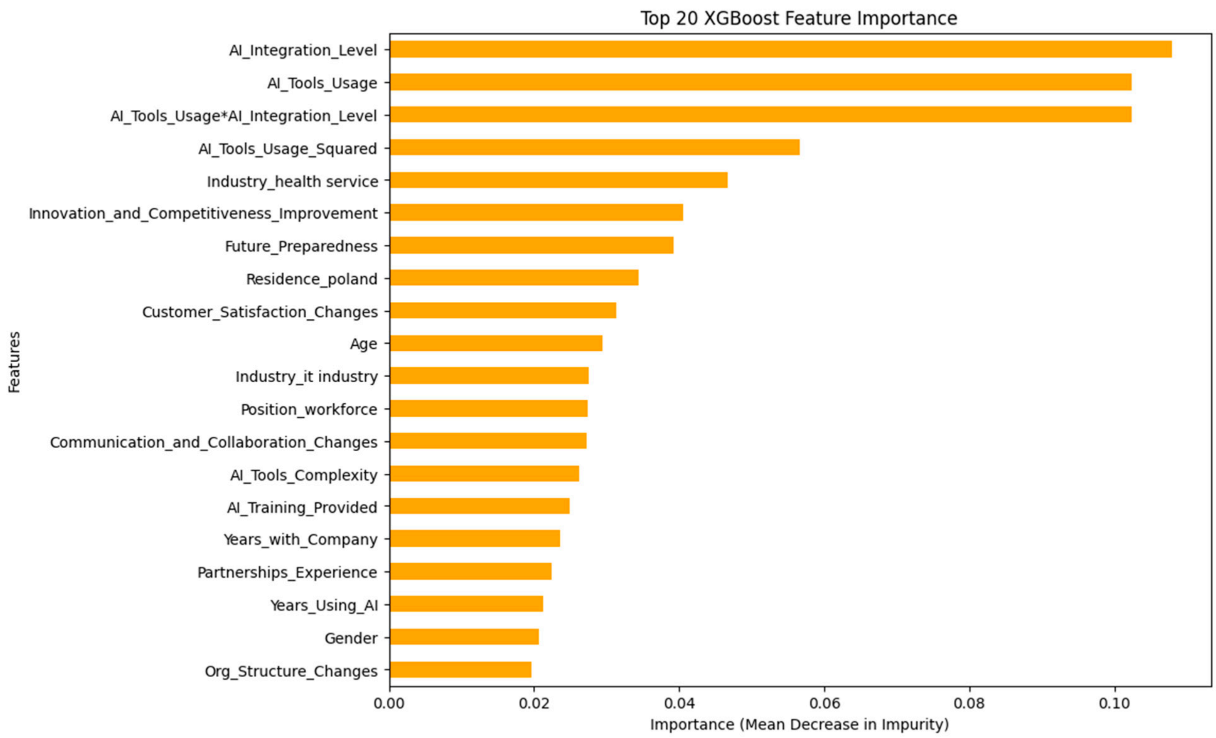

Figure 2. Top 20 XGBoost Feature Importance Top Features: AI_Integration_Level (significantly influences productivity changes), AI_Tools_Usage * AI_Integration_Level (suggesting that the combined

effect of these factors is important), and AI_Tools_Usage (the standalone effect of how frequently AI tools are used). Other Important Features: Polynomial terms like AI_Tools_Usage_Squared show the non-linear effects of AI tools usage; Innovation_and_Competitiveness_Improvement and Future_Preparedness indicate the importance of strategic factors in driving productivity changes. Demographic and categorical variables like Age, Years_with_Company, and Gender also play significant roles, but to a lesser extent.

The consistent importance of features like AI_Integration_Level, AI_Tools_Usage, and their interactions across both models highlights their critical roles in driving productivity changes. The importance of strategic factors (e.g., Innovation_and_Competitiveness _Improvement, Future_Preparedness) indicates that organizations' strategic approaches to AI integration significantly impact productivity outcomes.

While not as critical as the top features, demographic variables like Age, Years_Using _AI, and Years_with_Company still contribute to the model's predictive power. This suggests that personal and professional backgrounds also play a role in productivity changes.

4.3. Interpretation of LIME Values for Random Forest Model

In our analysis, we utilized LIME (Local Interpretable Model-agnostic Explanations) to interpret the model's predictions and gain insights into the contribution of each feature. This technique offered detailed explanations for individual predictions, enhancing our understanding of how different factors influenced the outcomes of our machine learning models.

Based on the aggregated LIME values, the features that have the most significant impact on the Random Forest model's predictions are presented in Figure 3, and the features for the XGBoost model are presented in Figure 4.

For the Random Forest model, the most influential features include the interaction between AI tools usage and AI integration level, AI integration level, and the squared term of AI tools usage. This indicates that both the extent of AI integration and the intensity of AI tools usage, especially when combined, play important roles in predicting productivity changes. Similarly, for the XGBoost model, the key features identified are the same interaction term, innovation and competitiveness improvement, and human resources industry, among others. This consistency across models underscores the importance of how extensively and intensively AI tools are used within the organization, as well as the perceived improvements in innovation and competitiveness. These insights suggest that organizations should focus on the comprehensive integration of AI tools and monitor their usage to maximize productivity benefits.

LIME's detailed feature importance with specific thresholds (e.g., "AI_Integration _Level > 0.74") provides a more nuanced understanding of feature impacts compared to the aggregate nature of model-derived importance.

4.4. Bayesian Network Modeling

Logistic regression identified key predictors like 'Age' and the interaction between 'AI Tools Usage' and 'AI Integration Level', but its linear nature limits its ability to capture more complex relationships. Random Forest and XGBoost models, while effective, highlighted the importance of non-linear interactions and feature importance, but their interpretability can be limited. The Bayesian Network approach addresses these limitations by explicitly modeling the probabilistic dependencies among all variables. It allows us to understand not just the direct effects of variables like 'Age' and 'AI Tools Usage', but also their indirect effects and interactions with other factors.

The next analysis involved the Bayesian model to understand predictors of productivity change. A Bayesian Network was constructed using the HillClimbSearch algorithm with the Bayesian Information Criterion (BIC) as the scoring metric. This approach iteratively explores possible network structures to maximize data fit while balancing model complexity and goodness-of-fit by penalizing overly complex models. Parameters were estimated through Maximum Likelihood Estimation (MLE), ensuring that the conditional probability distributions (CPDs) accurately reflect the observed relationships. Inference was performed using Variable Elimination, which enables exact probabilistic reasoning within the network. This method effectively handles the complex dependencies among ordinal variables, binary encodings, and interaction terms in the dataset. To evaluate the model's performance, a 5-fold cross-validation approach was employed, mitigating overfitting risk and providing reliable metrics.

The learned structure of the Bayesian Network revealed significant relationships between variables. Notably, 'AI_Tools_Usage' demonstrated a direct influence on P (Productivity_Change_Binary | AI_Tools_usage). Additionally, interactions were observed between 'Innovation_and_Competitiveness_Improvement' and 'Job_Opportunities_Creation' P(Opportunities_Creation | Innovation_and_Competitiveness_Improvement), highlighting the complex interdependencies in the data.

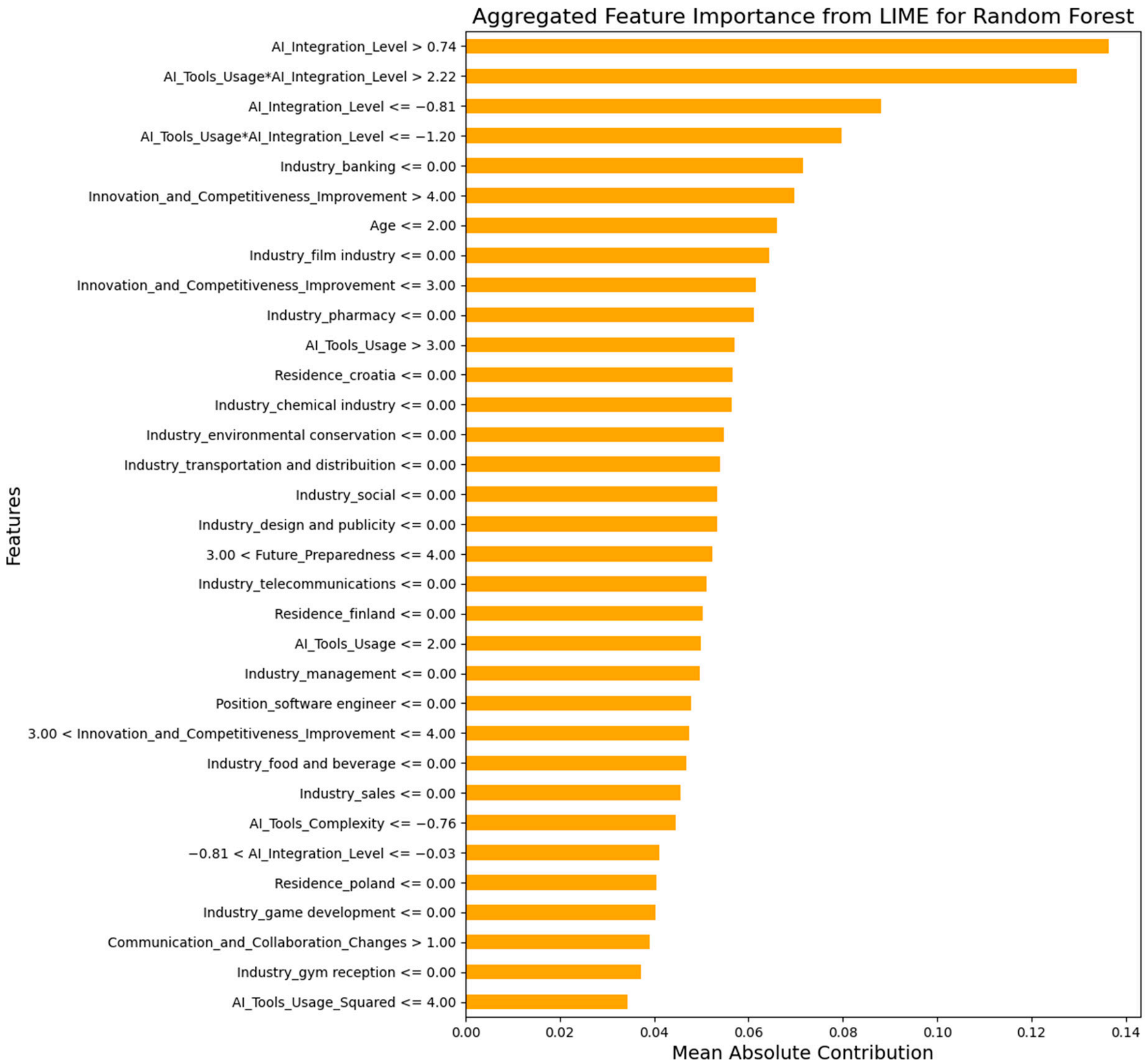

Figure 3. Aggregated feature importance from LIME for Random Forest.

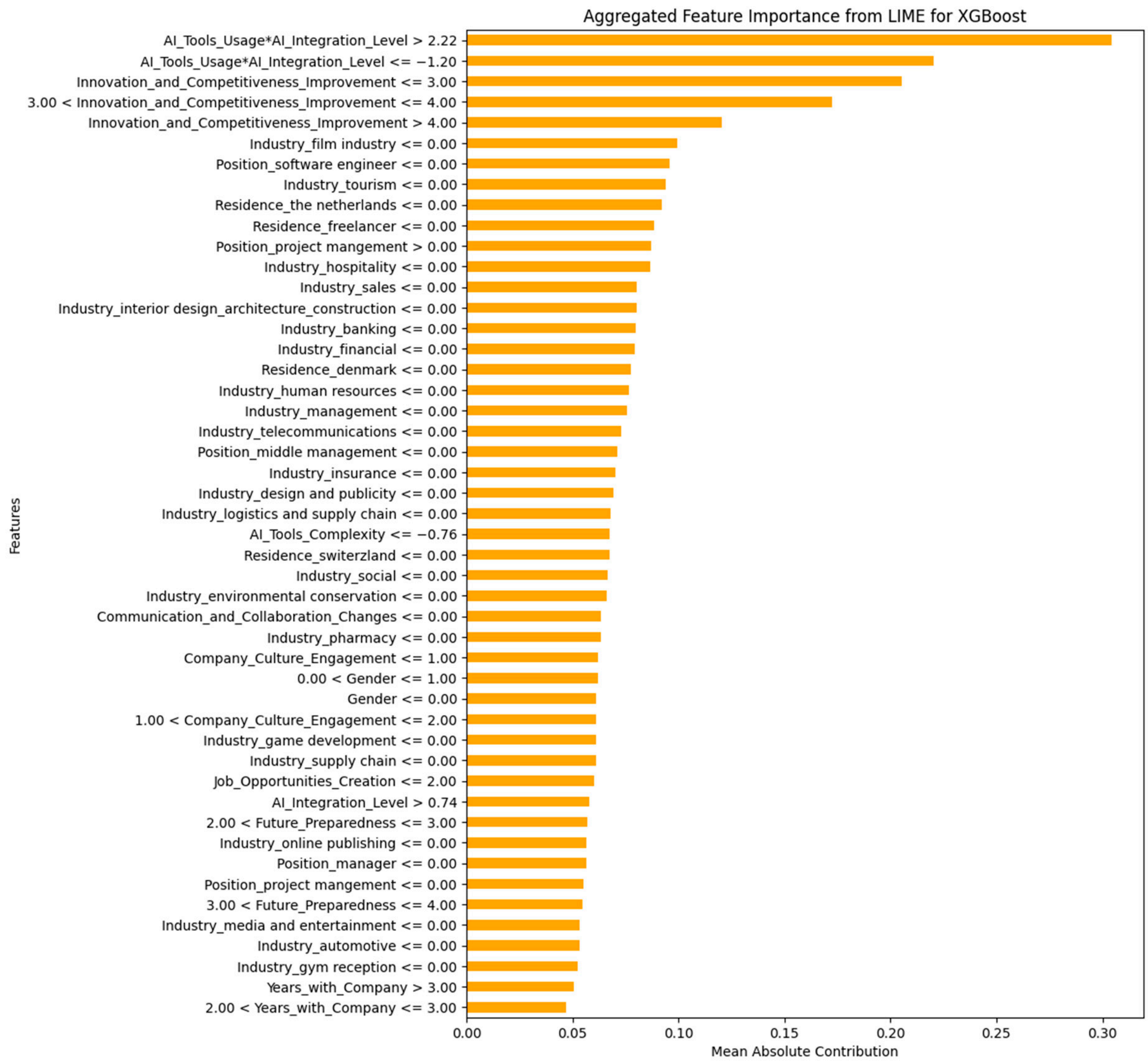

Figure 4. Aggregated feature importance from LIME for XGBoost.

Notably, the interaction between AI tools usage and AI integration level emerged as a critical predictor, indicating that the combined effect of these two factors significantly influences productivity outcomes. This finding is supported by the high conditional probabilities and the frequent appearance of AI-related features in the learned structure. Additionally, features such as ethical policy implementation and future preparedness were closely linked, suggesting that organizations with well-developed ethical considerations are better prepared for future challenges and are likely to experience positive productivity changes.

Demographic and categorical variables also played a significant role in shaping productivity outcomes. For example, the analysis showed that the residence of employees (such as those in Romania, Greece, and Canada) and industry sectors (like IT, telecommunications, and environmental conservation) influenced productivity changes. This highlights the importance of geographical and sectoral contexts in the implementation of AI tools. The network structure also pointed to the interconnectedness of various industry sectors, with the IT industry frequently linked to other sectors like public service and health service, emphasizing the widespread impact of IT on different areas. Overall, the Bayesian network provided a comprehensive view of how different factors interact and contribute to productivity changes, emphasizing the multifaceted nature of AI integration in the workplace.

To evaluate the predictive capability of the network, it was queried to determine the probability of productivity change given specific evidence. Based on the feature importance and LIME values from the XGBoost and Random Forest models, several queries were constructed to explore different scenarios (Table 6).

Table 6. Analysis of probabilities and interpretations of productivity change based on various factors.

Query	Evidence	Productivity_Change_Binary_0	Productivity_Change_Binary_1	Interpretation
1	{'AI_Tools_Usage': 3, 'Innovation_and_Competitiveness_Improvement': 4}	0.392	0.608	Higher probability of productivity change with moderate AI tools usage and high innovation improvement.
2	{'Ethical_Policies_Implementation': 2, 'AI_Integration_Level': 2.289}	0.493	0.507	Slightly higher probability of productivity change with full ethical policy implementation and high AI integration level.
3	{'Education': 4, 'Job_Opportunities_Creation': 3}	0.721	0.279	Lower probability of productivity change with high education level and neutral job opportunity creation.
4	{'Company_Culture_Engagement': 3, 'Communication_and_Collaboration_Changes': 2}	0.594	0.406	Moderate probability of productivity change with significant culture engagement and some collaboration changes.
5	{'AI_Training_Provided': 2}	0.718	0.282	Lower probability of productivity change with comprehensive AI training provided.
6	{'AI_Integration_Level': 2.289, 'Innovation_and_Competitiveness_Improvement': 5}	0.269	0.731	High probability of productivity change with high AI integration level and maximum innovation improvement.
7	{'AI_Tools_Usage': 4, 'Ethical_Considerations': 4}	0.280	0.720	High probability of productivity change with extensive AI tools usage and ethical considerations.
8	{'Job_Opportunities_Creation': 5, 'Company_Culture_Engagement': 3}	0.491	0.509	Slightly higher probability of productivity change with maximum job opportunity creation and significant culture engagement.
9	{'AI_Integration_Level': −1.197, 'Innovation_and_Competitiveness_Improvement': 1}	0.966	0.034	Very low probability of productivity change with minimal AI integration and low innovation improvement.
10	{'AI_Tools_Usage': 3, 'Future_Preparedness': 5}	0.475	0.525	Moderate probability of productivity change with moderate AI tools usage and high future preparedness.

Queries involving high levels of AI tools usage and AI integration show a notable likelihood of positive productivity change. For instance, when AI tools usage is high and ethical considerations are extensively addressed (Query 7), there is a significant 72.0% probability of productivity change. Similarly, a high AI integration level coupled with maximum innovation and competitiveness improvement (Query 6) yields a 73.1% probability of productivity change. These findings underscore the importance of comprehensive

AI adoption and strong ethical frameworks in driving productivity enhancements within organizations. Additionally, the interaction between AI integration and innovation appears important, as seen in the moderate probabilities of productivity change even with substantial AI tools usage and future preparedness (Query 10), emphasizing the need for balanced and well-integrated AI strategies.

Conversely, scenarios with minimal AI integration and low innovation improvement exhibit low probabilities of productivity change. Query 9, for instance, demonstrates a starkly low 3.4% probability of productivity change when AI integration is minimal and innovation improvement is low. This highlights the potential stagnation in productivity when AI tools and innovative practices are underutilized. Moreover, the findings suggest that even with high education levels and moderate job opportunity creation (Query 3), the probability of productivity change remains relatively low at 27.9%, indicating that factors like AI integration and ethical considerations may play more important roles in driving productivity. Overall, the results advocate for robust AI integration, ethical policy implementation, and continuous innovation as critical levers for enhancing productivity in modern workplaces.

The Bayesian Network model effectively captures the intricate relationships between variables, providing a robust framework for predicting productivity outcomes. These insights can guide organizations in optimizing their AI adoption strategies by focusing on key factors such as AI tools usage, innovation, ethical policies, education, company culture, and AI training.

In order to validate the robustness and generalizability of the Bayesian Network model constructed to predict productivity changes based on various organizational and individual factors, a k-fold cross-validation approach was employed. A 5-fold cross-validation (k = 5) was implemented using the KFold method from scikit-learn, ensuring that the dataset was split into 5 equal parts with shuffling enabled (random_state = 1). For each fold, the training subset was used to learn the structure and parameters of the Bayesian Network using the HillClimbSearch algorithm and BicScore for scoring. The MaximumLikelihoodEstimator was employed for parameter learning, and inference was performed using the VariableElimination method. State names for each variable were obtained, and evidence values were mapped to valid states within the range for each variable to ensure accurate inference. The cross-validation ROC results across the 5 folds were averaged to provide a comprehensive evaluation of the model's performance. The ROC AUC score of 0.7970 ± 0.0832 and the accuracy of 0.7817 ± 0.0694 demonstrate a strong ability of the model to discriminate between significant and non-significant productivity changes, highlighting the model's overall discriminative power.

These results validate the Bayesian Network model as a robust predictive tool for assessing productivity changes based on the provided evidence. The high recall and ROC AUC scores are particularly noteworthy, suggesting the model's potential utility in applications where identifying significant productivity changes is critical.

4.5. ROC Curve Comparison for Predictive Models

To evaluate the performance of the machine learning models used in this study, we generated ROC curves for Logistic Regression, Random Forest, XGBoost, and Bayesian Network (Figure 5). ROC curves provide a visual representation of the models' ability to discriminate between productivity changes and non-changes by plotting the True Positive Rate (Sensitivity) against the False Positive Rate (1—Specificity) across various threshold values. The Area Under the Curve (AUC) serves as a summary metric of the model's performance.

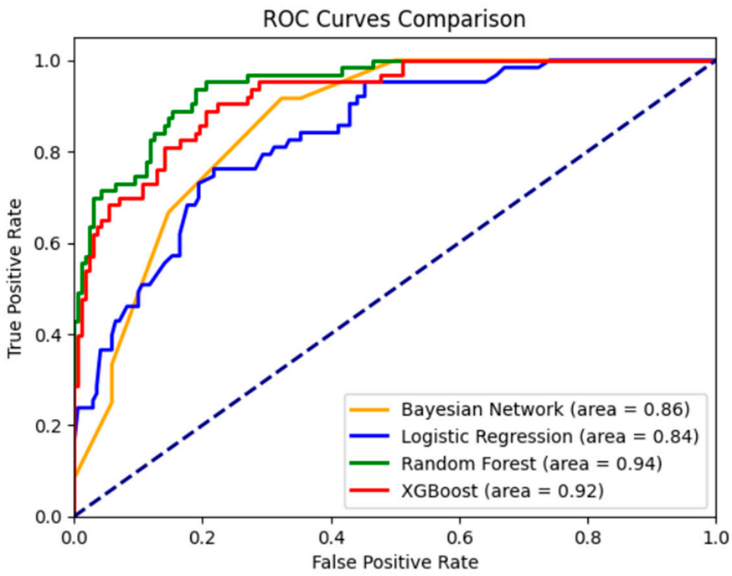

Figure 5. ROC curve comparison of Bayesian Network, Logistic Regression, Random Forest, and XGBoost models for predicting productivity changes.

As illustrated in Figure 5, the Random Forest model outperformed the others with an AUC of 0.94, indicating excellent performance in distinguishing between significant and non-significant productivity changes. XGBoost followed closely behind with an AUC of 0.92, confirming its ability to model complex relationships in the data. The Bayesian Network model achieved an AUC of 0.86, which reflects strong performance but is lower than the tree-based models. Logistic Regression, while effective, had the lowest AUC at 0.84, consistent with its more linear assumptions about the relationships between features and productivity changes.

The close proximity of the ROC curves for Random Forest and XGBoost models emphasizes the strength of ensemble methods in capturing non-linear interactions and complex feature dependencies in the dataset. Notably, the Bayesian Network model also exhibited a good ability to predict productivity changes, highlighting its strength in modeling probabilistic dependencies between variables. Logistic Regression, though slightly outperformed, still showed an adequate level of discrimination, particularly given its simplicity compared to the other methods.

The comparative analysis suggests that Random Forest and XGBoost, with their higher AUCs, are better suited for predicting significant productivity changes in this context, especially when complex interactions between AI tools usage and organizational factors are present.

5. Discussion

The findings of this study provide important insights into the economic impacts of AI on productivity across various organizational contexts. Several key observations emerge from the analysis, highlighting the significance of AI integration and its interplay with other organizational factors in driving productivity changes.

5.1. Key Findings and Their Implications

The most critical finding is that the interaction between AI tools usage and AI integration level significantly enhances productivity. The logistic regression model with interaction terms demonstrated that high levels of AI tools usage, combined with thorough integration within organizational workflows, result in substantial productivity improvements. This underscores the importance of not only adopting AI tools but also ensuring their comprehensive integration within organizational systems. The positive coefficient (β = 0.4319) for this interaction term signifies that increased usage and higher integration levels collectively enhance productivity.

Additionally, the age of employees emerged as a significant predictor of productivity changes, with older age groups associated with lower productivity improvements. This suggests that younger employees might be more adaptable to AI tools or that there might be generational differences in how AI technologies are utilized and embraced in the workplace. These insights highlight the need for targeted training programs that cater to different age groups to maximize AI's benefits.

5.2. Comparison with Previous Studies

While this study contributes valuable insights into the impact of AI tools on employee productivity, it is important to situate the findings within the broader context of existing research. A significant body of literature has examined the ways AI technologies influence productivity across various industries and sectors. Authors such as Brynjolfsson and McAfee (2014) [12] have extensively studied the "productivity paradox" in AI adoption, where rapid advancements in technology have not immediately translated into observable productivity gains in many sectors. In contrast, more recent studies, such as those by Czarnitzki et al. (2023) [5], found evidence of AI-driven productivity growth at the firm level, particularly in technology-intensive industries.

The results align with the theoretical perspectives proposed by [2,3], which suggest that AI can enhance productivity by improving decision-making and operational efficiencies. The shift from mid-skill to high-skill and managerial positions reported by [13] also supports our findings that AI integration fosters higher productivity, particularly in more complex and strategic roles.

However, our study presents a more nuanced view compared to the mixed empirical results reported in the previous literature. For instance, while [19] found significant increases in patents and trademarks associated with AI but no increase in sales per worker, our findings highlight the critical role of AI integration in realizing productivity gains. This suggests that the benefits of AI may not solely depend on innovation outputs but also on how well AI tools are embedded within organizational processes.

Unlike some studies that suggest AI's productivity gains are mainly concentrated in specific high-tech industries (Calvino and Fontanelli, 2023) [9], our research reveals that AI's positive impact extends across a diverse range of sectors. This suggests that AI's influence on productivity is not limited to technology-heavy fields but can be observed in traditional industries as well, provided that AI tools are well-integrated into daily operations.

The "productivity paradox" has been a central theme in AI research, where advancements in AI technology often do not translate into immediate productivity improvements at the macroeconomic level. Studies by Parteka and Kordalska (2023) [21] have discussed this phenomenon in depth, pointing to the slow diffusion of AI technologies across industries and the time lag before benefits materialize. Our study addresses this by focusing on firm-level data and examining productivity changes that occur once AI tools are fully integrated into workflows. The interaction terms between AI tools usage and AI integration in our models demonstrate that productivity gains are realized when there is comprehensive, rather than superficial, AI adoption.

This study applies Bayesian Network Analysis to explore probabilistic dependencies and predict AI's impact on employee productivity, highlighting the value of robust forecasting in AI-driven environments. This aligns with other authors' approaches [30].

While there is substantial literature on AI and productivity, this study makes original contributions by using advanced analytical techniques such as Bayesian Network Analysis and machine learning models, including Random Forest and XGBoost, to explore complex interdependencies. Unlike many studies that rely solely on traditional econometric methods, our approach captures non-linear relationships between variables, revealing that the interaction between AI tools usage and organizational AI integration levels is a critical driver of productivity.

Additionally, our study highlights generational differences in AI adaptability—an area that remains underexplored in the current literature. As our analysis shows, younger employees experience greater productivity gains from AI tools compared to their older counterparts. This suggests that future research should examine not only the technical aspects of AI adoption but also the demographic factors that influence how AI impacts productivity across various employee groups.

5.3. Strengths and Limitations

One of the strengths of this study is the comprehensive dataset obtained from a diverse sample of employees across various industries. The use of advanced modeling techniques, such as logistic regression with interaction terms, Random Forest, and XGBoost, provides robust insights into the factors driving productivity changes. The inclusion of interpretability techniques like SHAP and LIME further enhances the transparency and understanding of model predictions.

However, the study also has limitations. The reliance on self-reported data from the questionnaire may introduce biases related to respondents' perceptions and experiences. Despite efforts to ensure a representative sample, there may be inherent biases in the data that could affect the generalizability of the findings. Additionally, the cross-sectional nature of the data limits the ability to infer causal relationships between AI usage and productivity changes. While the sample size of 233 responses provides a solid basis for statistical analysis, it may not fully represent the broader workforce. Certain industries or employee groups might be underrepresented, limiting the ability to generalize the findings to other sectors or populations. Additionally, the global diversity of respondents introduces potential regional variations in AI adoption and impact, which may not be fully accounted for in this analysis. Finally, the study does not delve deeply into the potential ethical concerns or organizational challenges associated with AI integration, such as data privacy, transparency, or employee resistance. These factors could significantly affect the success of AI implementation and its overall productivity outcomes, highlighting a need for future research to address these complexities.

5.4. Unexpected Outcomes and Inconclusive Results

Some unexpected outcomes include the relatively low probability of productivity change even with high education levels and moderate job opportunity creation. This suggests that factors like AI integration and ethical considerations may play more important roles in driving productivity than initially anticipated. Furthermore, the relatively lower recall for the positive class (0.52) in the logistic regression model indicates that there may be other unobserved factors influencing productivity changes that were not captured in the study.

The Bayesian Network analysis provided additional insights by capturing the intricate relationships between variables and offering a robust framework for predicting productivity outcomes. Queries involving high levels of AI tools usage and integration consistently showed high probabilities of productivity change, emphasizing the importance of a well-rounded AI strategy.

6. Conclusions

The study successfully addresses and provides evidence for the hypotheses through comprehensive data analysis and advanced modeling techniques. Below is a breakdown of how each hypothesis was supported:

Hypothesis 1. *High levels of AI tool usage and comprehensive integration within organizational workflows significantly enhance productivity.*

Evidence

1. Logistic Regression Analysis: The logistic regression model with interaction terms identified significant predictors of productivity change, including the interaction between AI tool usage and AI integration level. The positive coefficient for this interaction term ($\beta = 0.4319$, $p < 0.001$) demonstrates that frequent AI tool usage combined with high integration levels significantly increases productivity.
2. Random Forest and XGBoost Models: These models captured non-linear relationships and interactions between features, consistently highlighting the importance of AI integration level and AI tools usage as top predictors of productivity change.
3. LIME Interpretation: The Local Interpretable Model-agnostic Explanations (LIME) provided detailed insights, confirming that the interaction between AI tools usage and integration level plays an important role in enhancing productivity.

Hypothesis 2. *The impact of AI on employment is complex, with positive productivity effects at the firm level not necessarily translating into negative employment effects at the aggregate level.*

Evidence

1. Descriptive and Inferential Statistics: The study presented mixed results on AI's impact on employment, reflecting its complexity. While some firms experienced productivity gains, these did not uniformly translate into job losses.
2. Empirical Studies: The literature review cited studies indicating that AI-using firms often experience positive productivity effects without significant negative impacts on overall employment [5]. This supports the hypothesis that AI can complement human labor, leading to job augmentation rather than straightforward job displacement.

Hypothesis 3. *The benefits of AI integration are moderated by factors such as AI complexity, areas of AI utilization, and employee characteristics.*

Evidence

1. Logistic Regression with Interaction Terms: The analysis included interaction terms between AI tools usage, AI integration level, and AI tools complexity. The results showed that these interactions significantly impact productivity outcomes, with the interaction between AI tools usage and integration level being particularly influential.
2. Bayesian Network Analysis: This analysis revealed significant relationships between various factors, including AI tools usage, innovation, competitiveness improvement, and demographic variables such as age. The Bayesian network highlighted how these factors interact and collectively influence productivity changes.
3. Feature Importance Analysis: Techniques like SHAP and LIME were used to interpret the models, identifying key factors that moderated the benefits of AI integration, such as the complexity of AI tools and the context in which they are used.

This study confirms the hypothesis that AI holds significant promise for enhancing economic growth and productivity, with its outcomes influenced by factors such as industry context, regulatory frameworks, and human labor complementarity. Key findings indicate that high levels of AI tools usage and comprehensive integration within organizational workflows significantly enhance productivity. Younger employees tend to experience greater productivity gains from AI tools compared to older age groups, highlighting generational differences in adaptability. Additionally, organizations with robust ethical policies and innovative practices are better positioned to realize AI's productivity benefits.

6.1. Major Findings and Contributions

The study's major findings include:

1. Enhanced Productivity: The interaction between AI tools usage and integration levels significantly boosts productivity.

2. Generational Impact: Younger employees adapt more effectively to AI tools, resulting in higher productivity gains.
3. Ethical Frameworks: Ethical policy implementation and continuous innovation are critical for maximizing AI's benefits.

These findings contribute to existing knowledge by aligning with theoretical perspectives on AI's potential to improve decision-making and operational efficiencies. The study provides empirical evidence supporting the critical role of AI integration in productivity gains. It also addresses measurement challenges and emphasizes the need for refined frameworks to capture AI's intangible benefits and align AI adoption with human capabilities.

6.1.1. Theoretical Significance

This research provides a critical contribution to the theoretical understanding of AI's role in modern economies. By combining traditional economic theories of productivity with advanced machine learning techniques, such as Random Forest, XGBoost, and Bayesian Network Analysis, this study extends existing frameworks to account for the complex and dynamic interactions between AI adoption and productivity. The findings also support theoretical perspectives that suggest AI, when well-integrated, complements human labor, fostering greater innovation and decision-making capabilities. Furthermore, the study highlights the moderating effects of demographic and organizational factors on AI's productivity gains, adding depth to existing labor theories in the AI context.

6.1.2. Practical Significance

On a practical level, this research offers actionable insights for business leaders and policymakers. By demonstrating the critical importance of comprehensive AI integration and tailored employee training programs, the findings provide a roadmap for organizations seeking to maximize the benefits of AI adoption. The generational differences in adaptability to AI tools underscore the need for targeted strategies to ensure all employee groups benefit from AI technologies. Additionally, the emphasis on ethical AI frameworks and continuous innovation points to the broader organizational changes necessary for sustained productivity gains. Policymakers can draw from these insights to support AI-driven economic growth while addressing potential societal challenges, such as employment shifts and income inequality.

However, the study has certain limitations. The reliance on self-reported questionnaire data may introduce biases related to respondents' perceptions and experiences. Additionally, the cross-sectional design limits the ability to infer causal relationships between AI usage and productivity changes.

Future research should focus on conducting longitudinal studies that track the long-term effects of AI adoption on productivity and employee engagement. Longitudinal data would help establish causal relationships and provide insights into the sustainability of AI-driven productivity gains over time. Additionally, exploring the role of organizational culture, leadership practices, and employee morale in shaping AI adoption outcomes would offer a more holistic understanding of AI's influence in the workplace. Further studies could also investigate how AI impacts different sectors and industries to develop industry-specific strategies for AI implementation. Addressing the ethical implications of AI adoption, including issues such as bias, transparency, and accountability, would further enrich the discourse and guide policymakers in regulating AI to ensure fair and responsible usage.

As AI technologies continue to evolve, their integration into more complex and strategic roles could further amplify productivity gains and reshape labor markets. Future regulatory frameworks may need to adapt to ensure ethical AI usage and mitigate potential adverse effects on employment and income distribution.

This study confirms the hypothesis that AI significantly enhances productivity, particularly when AI tools are extensively used and well-integrated within organizational workflows. The findings emphasize the importance of strategic AI integration, targeted training programs for different age groups, and robust ethical frameworks to maximize AI's economic potential. Future research should address the identified limitations and explore broader contextual factors to provide a more comprehensive understanding of AI's impacts on productivity and economic growth. These conclusions are directly linked to the original research question and supported by the study's results.

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