AVE Trends in Intelligent Management Letters

Enhancing Productivity and Reporting Accuracy Through AI and BI Integration in U.S. Based Small Financial Firms

Md. Asif Hasan[1,*], Md. Tanvir Rahman Mazumder[2], Md. Caleb Motari[3], Md. Shahadat Hossain Shourov[4], Mrinmoy Sarkar[5]

[1,3]School of Business, Montclair State University, Montclair, New Jersey, United States of America.
[2,5]School of Information Technology, Washington University of Science and Technology (WUST), Alexandria, Virginia, United States of America.
[4]Department of Information Technology Management, Webster University, Webster Groves, Missouri, United States of America.
hasana10@montclair.edu[1], mtanvir.student@wust.edu[2], motaric1@montclair.edu[3], mshourov@webster.edu[4], msarkar.student@wust.edu[5]

*Corresponding author

Abstract: Due to a rise in data complexity and strict regulations, small financial firms in the US are now required to update their systems and procedures. It looks into the influence of combining Artificial Intelligence (AI) and Business Intelligence (BI) on productivity, accurate reporting, and confident decision-making in U.S.-based small and mid-sized financial firms. A cross-sectional survey was conducted to collect information from 400 financial professionals in various roles across companies of different sizes. According to the results, firms that work with AI and BI have better productivity and fewer mistakes in reporting than companies that do not use these technologies. The regression analysis proved that BI and AI played major roles in predicting performance, and the correlation analysis found a positive relationship between reporting and decision confidence ($r = 0.64$). The results of Exploratory Factor Analysis validated the model and indicated two distinct constructs: productivity and reporting accuracy, with a cumulative variance explained of 74.1%. There are still obstacles, like a lack of technical knowledge and integration issues, that many people face. The results provide useful directions for leaders, policymakers, and technology providers who wish to enhance the efficiency and regulatory compliance of small banks using AI and BI.

Keywords: Artificial Intelligence (AI); Business Intelligence (BI); Reporting Accuracy; Financial SMEs; Digital Transformation; U.S. Financial Sector; Decision-Making; Regulatory Compliance; Financial Firms.

Cite as: M. A. Hasan, M.T. R. Mazumder, M. C. Motari, M. S. H. Shourov, and M. Sarkar, “Enhancing Productivity and Reporting Accuracy Through AI and BI Integration in U.S. Based Small Financial Firms,” *AVE Trends in Intelligent Management Letters*, vol. 1, no. 2, pp. 59–75, 2025.

Journal Homepage: https://www.avepubs.com/user/journals/details/ATIML

Received on: 26/04/2024, **Revised on:** 20/06/2024, **Accepted on:** 21/08/2024, **Published on:** 05/06/2025

DOI: https://doi.org/10.64091/ATIML.2025.000136

1. Introduction

The financial services industry in the United States is changing rapidly due to increased regulations, clients' demand for clear information, and the challenge to act quickly in competition. Nowadays, both AI and BI are being used more often in businesses to improve processes, make data more accurate, and assist with effective planning [5]; [14]. They are modernising the handling of financial data and making reporting processes more automated, less reliant on human intervention, and more reliable for decision-making [16]. Even though numerous studies discuss how digitalisation helps large companies and big banks, not much research has been done on how small and mid-sized U.S. financial firms use digital technologies. It is expected of these firms to follow the same regulations as big companies, but their small scale and limited budgets usually make it difficult for them to invest in advanced AI/BI tools [8]; [18]. As a result, smaller firms deal with extra stress, mainly when working on real-time data, making financial statements, and preparing for internal audits.

Even though AI and BI are thought to improve small financial firms, there is little empirical data on their combined effects on productivity and reporting accuracy. So far, there has been limited research on how these tools influence the quality of operations and report preparation in small resource-poor organisations [2]; [1]. According to Selvarajan [6] and Siddiqui [9], understanding the results of combining AI and BI helps companies develop effective plans for their use and protect their financial decisions in the future. This study examines whether combining AI and BI into the work of small banks in the US improves their productivity, accuracy in reporting, and confidence in making decisions. The authors surveyed 400 professionals from various positions and companies to study how AI has been used and the problems encountered. It notes that in the United States, regulatory organisations are increasingly urging AI systems to be both explainable and compliant [10]; [7]. The study supports both academics and policymakers by demonstrating how intelligent digital technologies can make America's small financial institutions more effective and better able to respond to regulations.

2. Literature Review

2.1. The Rise of AI and BI in Financial Services

There has been a significant increase in the use of Artificial Intelligence (AI) and Business Intelligence (BI) in the financial services industry, driven by recent advancements in data processing, machine learning, and automation technologies. With AI, banks can make intelligent choices with the help of real-time data modelling, predictive analytics, and robotic process automation [5]; [16]. BI tools, on the other hand, assist in turning raw data into useful information for a business by using visualisations, dashboards, and key performance indicators (KPI) [15]; [1]. In America, the need to implement these technologies arises from the desire to work more efficiently and to comply with growing regulatory rules. Power BI, Tableau, and AI-powered dashboard software are now being used to make financial reporting more transparent, faster, and in line with rules from the SEC and OCC [8]; [7]. For this reason, AI and BI have become important elements of today's financial strategy, especially for firms dealing with digital transformation and meeting current regulations [17].

2.2. AI and Productivity in Small Financial Firms

Various studies have observed that AI boosts a company's productivity, mainly in areas where most tasks are carried out manually. The use of RPA and machine learning automation eases routine jobs such as matching invoices, entering data, discovering fraud, and projecting trends, freeing up people to focus on other things [14]. In companies located in the U.S, where both staff and time are scarce, AI can make a big difference in productivity. According to Siddiqui [9], when AI is used in systems that feature process automation and decision guidance, it can result in up to 30% improvement in how smoothly the operations run. Mishra et al. [18] mention that with better predictions, AI helps businesses complete their tasks more rapidly and accurately, thereby supporting agility. Gaining such benefits can mean the difference between a small firm's success and failure in the long run.

2.3. The Role of BI in Reporting Accuracy and Compliance

BI systems make it possible to confirm the precision and consistent nature of financial records. They enable companies to collect information from several systems, apply defined business rules, and immediately produce compliant reports. Alao et al. [11] state that BI tools minimise errors by automatically checking and normalising data. According to Selvarajan [6], since BI platforms enable detailed data checking and analysis with visual tools, they help reduce risks. This is important for small financial companies because, lacking their own compliance teams, they depend on automated and practical BI dashboards for risk management.

2.4. Integrated AI–BI Systems and Organisational Decision-Making

The use of AI and BI together integrates predictive analytics and real-time reporting into a single system to support decision-making. In their book, Chintala and Thiyagarajan [16] call this process "cognitive business intelligence," since AI is used to improve the logic of BI dashboards and BI sets the results of AI in a way that supports decision-making. Famoti et al. [12] state that this convergence helps achieve higher efficiency and supports managers' confidence and teamwork. The authors explain that integrated systems give teams a way to learn and improve the system over time. Small financial firms benefit from this integration by responding more swiftly to market changes, acting faster on unusual events, and more accurately estimating their clients' financial actions. Victor-Mgbachi [20] mentions that through such systems, humans are less likely to depend on intuition alone and can make fairer decisions in important cases.

2.5. Barriers to Adoption in U.S. Small Financial Firms

Although AI and BI offer many benefits, small financial institutions do not embrace them as much as larger ones. Issues that need to be addressed include the high cost of implementation, a shortage of skilled professionals, the integration of different systems, and resistance to using technology at work [19]; [2]. Even in advanced countries like the United States, many small firms face challenges with outdated systems, have very few IT specialists, and fail to recognise the value of digital tools [13]; [7]. According to Victor-Mgbachi [20], the use of the best technology will remain limited if users do not get proper onboarding and training. Many times, smaller firms need help from public programs and industry partners to fill the gap in their abilities when they try to add AI to their financial reporting [8]. According to Victor-Mgbachi [20], overlooking ethical, data privacy, and explainability issues may result in both non-compliance and the lack of stakeholders' trust—risks that are even greater in small companies with few resources in legal or risk management.

2.6. Summary of Literature Gaps

Many studies confirm that AI and BI are valuable on their own. Still, there is little research on how they collaboratively affect the productivity, reporting accuracy, and confidence in decision-making of small U.S. financial firms. Most of the literature examines big companies or ideas, but it does not explain how these technologies are used in real life when facing limited finances, small groups, and strict rules.

3. Methodology

3.1. Research Design

The researchers used a quantitative, cross-sectional survey design to learn how AI and BI integration influences productivity, report accuracy, and decision-making confidence in small U.S. financial firms. The chosen design was appropriate for assessing real-world changes in organisations and testing how technology adoption relates to their performance. The study focused on expressions from financial experts to develop results that benefit both academics and practitioners. Since the survey was structured, it became possible to conduct correlation, regression, and factor analysis.

3.2. Population and Sampling

The study focused on professionals employed in small and mid-sized financial organisations in the United States, working in accounting, compliance, finance, IT, and executive leadership. People involved in or knowledgeable about their firm's AI and BI tools were selected using non-probability purposive sampling. A total of 400 responses were analysed, providing a comprehensive and reliable picture of the sector. Only people employed in firms with fewer than 500 workers, who use U.S. regulations and who have experience with financial technology, were considered eligible for the study. This organisation of the study made it possible to draw valid conclusions and use the data for statistical examination (Figure 1).

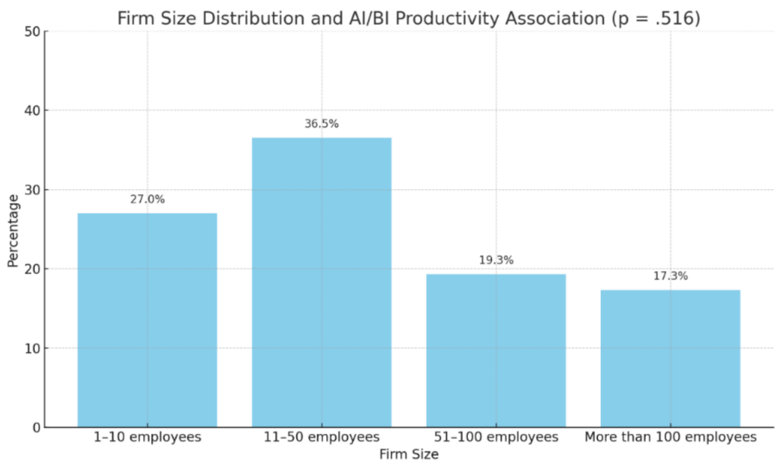

Figure 1: Firm size distribution and AI/BI productivity association (p = .516)

3.3. Instrumentation

To gather information, a well-organised questionnaire was designed to examine six areas: respondent background, AI/BI use, productivity changes, improvement in reporting, confidence in decision making, and difficulties implementing AI/BI. Binary options, multiple-choice questions, and Likert-scale were the main items used, where participants could select from 1 (Strongly Disagree) to 5 (Strongly Agree). They were based on existing research about digital transformation in finance and were first tested with some professionals to check that they made sense. Psychometric validity was demonstrated by the data, as measured by EFA, which identified two reliable components: Productivity and Reporting Accuracy. These components explain 74.1% of the total variance with only minimal cross-loading. The KMO of 0.873 and the significance of Bartlett's Test proved that the instrument is suitable for multivariate analysis.

3.4. Data Collection Procedure

Data was gathered by sending an online survey to people on LinkedIn groups, financial associations, and targeted mailing lists. Six weeks were allocated for the collection process, which was enough time to find participants and follow up on their surveys. People were free to take part, and each one was told about the study goals, how data would be kept safe, and how their answers would stay private. There was no personal information in the data, and it was kept in a secure digital place that no one else could use. Because the training was held online, it was possible to include learners from different parts of the world and at different times.

3.5. Data Analysis

All the collected data were examined using IBM SPSS. A summary of the demographic and organisational features of the sample was created using descriptive statistics. Data was analysed using chi-square tests to find out how job role, firm size, and technology adoption are associated. Pearson correlation coefficients were used to assess the strength and direction of the relationships between AI/BI usage, productivity, reporting accuracy, and decision-making confidence. To make the predictions, multiple linear regression analysis was carried out by considering AI, BI, firm size, and training as independent variables. EFA was conducted to check the reliability and the way the survey was constructed. Statistical reliability of the results was confirmed by performing all analyses at a 95% confidence level ($p < 0.05$).

3.6. Ethical Considerations

This study followed the usual ethical rules used in social science research. Each person was notified that their involvement was entirely voluntary and that the information they provided would not be disclosed to anyone. The survey included a statement at the beginning that outlined the purpose of the study, the methods for ensuring data protection, and the ability for participants to withdraw at any time. Since the research was anonymous and did not disturb the participants, it was not necessary to get permission from an IRB.

3.7. Research Gap: AI and BI Integration in U.S.-Based Financial SMEs

Although extensive research has been conducted on digital transformation in large financial organisations, there remains a lack of information on how AI and BI collaborate in practice for small and mid-sized financial firms in the United States. Even though large financial groups can use advanced analytics and automation, smaller organisations struggle because they have less advanced technology, fewer resources, and more scattered data. It is common for existing research to mix results for all kinds of firms, without considering the specific needs and regulations of American financial SMEs [9]; [7]. Besides, there are not many studies showing how the combined use of AI and BI improves aspects such as productivity, reporting accuracy, and decision confidence among these companies. This research fills this gap by offering U.S. information and analysis on how AI/BI is applied in practice and what opportunities it creates for small banks and credit unions in the country. The findings aim to shape academic discussions and influence U.S. policies that help SMEs advance with digital progress, comply with the law, and innovate.

4. Results

4.1. Demographic Profile and Its Association with Technology Adoption

Table 1 shows that most of the participants in the sample were Finance and Accounting staff (48.5%), second were Executive Management (31.3%), and third were IT/Technology staff (20.3%). It was found that the role an employee has does not greatly affect their use of AI and BI tools or their opinion of the accuracy of the reports ($p > .05$). Out of all the respondents, 35.3%

belonged to firms that were 4–7 years old, and 26% were from firms that had been operating for 1–3 years. Nearly nine percent of firms had been operating for less than one year, whereas 29.8% were more than seven years old.

Table 1: Demographics of respondents and their associations with technology adoption

Variable	Categories	Frequency	Percent	Chi-Square Association (p-value)
Role	Executive Management	125	31.3%	
	Finance/Accounting Staff	194	48.5%	
	IT/Technology Staff	81	20.3%	With AI Use: p = .929
				With BI Use: p = .899
				With Confidence: p = .414
Firm Age	Less than 1 year	36	9.0%	With BI Streamlining: p = .177
	1–3 years	104	26.0%	
	4–7 years	141	35.3%	
	More than 7 years	119	29.8%	
Firm Size	1–10 employees	108	27.0%	With AI/BI Productivity: p = .516
	11–50 employees	146	36.5%	
	51–100 employees	77	19.3%	
	More than 100 employees	69	17.3%	

Still, there was no strong connection found between a firm's age and its perception of streamlining from BI (p = .177). Statistics on firm size indicate that 36.5% of the respondents worked at firms with 11–50 employees, and 27% represented micro firms with less than 10 employees. Out of all the businesses analysed, 17.3% had more than 100 employees. The connection between firm size and technology's effect on productivity was not proved (p = .516), indicating that the degree of productivity from technology depends more on factors apart from firm size (Figure 2).

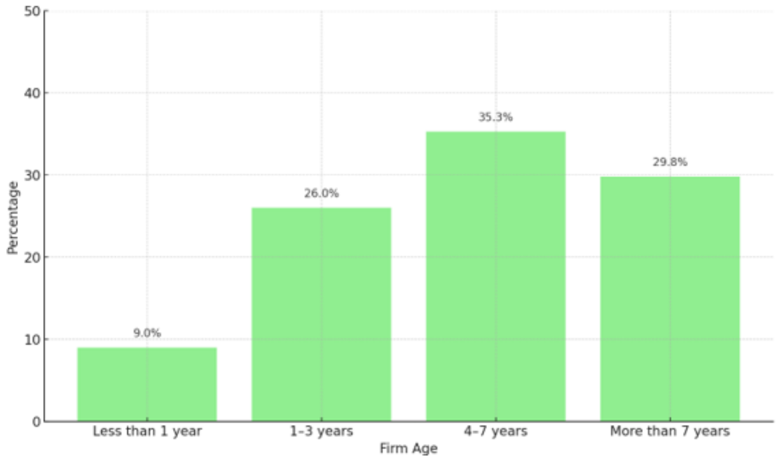

Figure 2: Firm age distribution

4.2. AI and BI Usage Patterns and Their Organisational Impact

Table 2 provides details about the adoption of AI and BI and their connection to various factors in organisations. About two-thirds of respondents said their firm applies AI, and 70% of them named Business Intelligence (BI) as a main tool they use. Even though the number of users is high, chi-square tests did not reveal any significant impact of AI on confidence in reports (p = .689) or training (p = .418). In the same way, neither BI tool usage nor report confidence was strongly related to whether someone preferred support mechanisms (p = .541 and p = .941).

Table 2: AI and BI technology usage and associated factors

Variable	Categories	Frequency	Percent	Chi-Square Association (p-value)
AI Tool Usage	Yes	257	64.3%	With Confidence: p = .689
	No	143	35.8%	With Training: p = .418
BI Tool Usage	Yes	280	70.0%	With Confidence: p = .541

	No	120	30.0%	With Support Preference: p = .941
Type of AI Tool	None	168	42.0%	With Workload Reduction: p = .237
	RPA	95	23.8%	
	ML Analytics	77	19.3%	
	Chatbots	60	15.0%	
Type of BI Tool	None	137	34.3%	With Confidence: p = .047
	Power BI	146	36.5%	
	Tableau	81	20.3%	
	QlikView	36	9.0%	

The most frequently used AI tool by organisations was Robotic Process Automation (RPA), with Machine Learning-based Analytics and Chatbots or virtual assistants coming in second and third. Still, 42% of the respondents said they have not introduced any AI tool to their company. It seems that the variety of AI tools available did not have a big impact on workload reduction (p = .237), which means perceived benefits can come from all AI tools. Among the BI tools, most people preferred Power BI (36.5%), followed by Tableau (20.3%) and QlikView (9%). 34.3% of people surveyed indicated they do not have any BI platform. It was also found that the type of BI tool used had a significant tie to confidence in reporting (p = .047), demonstrating that some platforms make users more confident about the accuracy of their data (Figure 3).

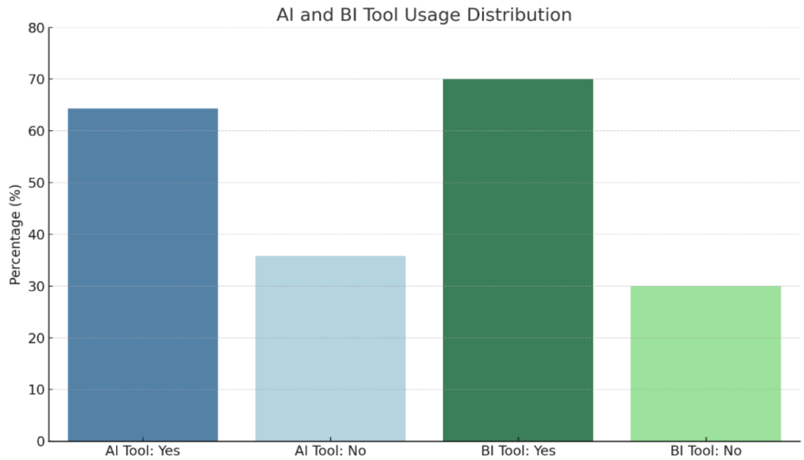

Figure 3: AI and BI tool usage distribution

4.3. Perceived Impact of AI and BI on Productivity

According to Table 3, there were very positive perceptions of productivity due to AI and BI technologies across all evaluated aspects. In the survey, 68.2% of respondents felt that AI boosts how work is done, and 69.3% thought that BI simplifies reporting procedures. Also, 67.7% of participants believed that the use of AI and BI reduces manual work, and 69.0% agreed that it accelerates decision-making in their companies.

Table 3: Perceived impact of AI and BI on productivity

Statement	Strongly Agree (%)	Agree (%)	Total Positive (%)	Chi-square p-value
AI improves operational productivity	39.5	28.7	68.2	-
BI streamlines reporting processes	41.5	27.8	69.3	-
AI/BI reduces manual workload	39.5	28.2	67.7	-
Faster decision-making with AI/BI	39.5	29.5	69.0	-
Employees adapt quickly to AI/BI	33.8	36.8	70.6	p = .047*

Note: *Asterisk indicates statistically significant relationship with confidence level (χ^2 test).*

Most people agreed that employees can quickly use AI and BI systems, with 70.6% expressing this opinion. It was found that those who adapt to new technologies are likely to trust AI/BI results more than others, with a statistically significant connection (p = .047). All in all, the data show that a majority of small U.S. financial firms support the benefits of AI and BI in making their operations more effective (Figure 4).

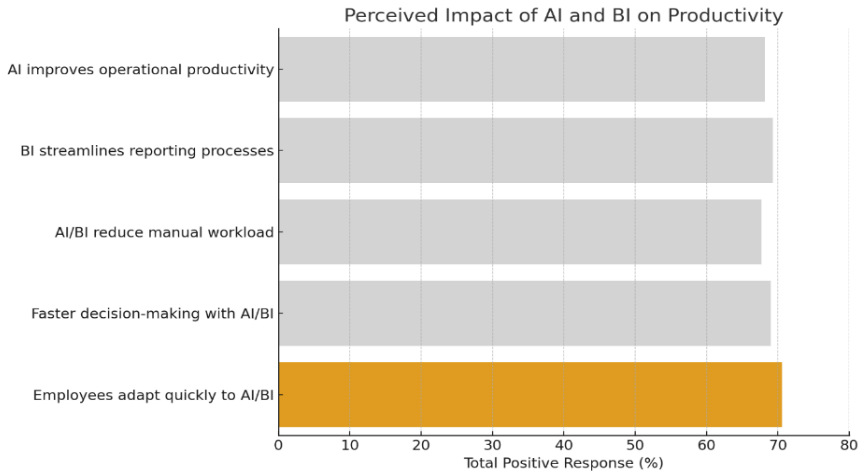

Figure 4: Perceived impact of AI and BI on productivity (horizontal view)

4.4. Perceived Improvements in Reporting Accuracy

The results in Table 4 indicate that most respondents view the combination of AI and BI as very beneficial to the accuracy of reporting. There is strong agreement among 68.7% of people that AI helps avoid errors in financial reporting. Seventy-two percent of respondents believed that BI makes data more accurate, which was the highest number for any statement in this category, even though it was not statistically proven (p = .157).

Table 4: Perceived improvements in reporting accuracy

Statement	Strongly Agree (%)	Agree (%)	Total Positive (%)	Chi-square p-value
AI reduces reporting errors	40.5	28.2	68.7	-
BI improves data accuracy	38.5	33.8	72.3	p = .157
Automated validation improves accuracy	39.8	29.3	69.1	-
Fewer inconsistencies in reports	40.3	29.0	69.3	-
Reduced compliance risks with AI/BI	39.0	30.8	69.8	-

Most participants believed that automating data validation led to better accuracy, with 69.1% of respondents agreeing. Besides, 69.3% experienced less variation among their firm's reports, and 69.8% believe that using AI and BI together helps address compliance-related risks. Even though none of these relationships were significant at the most common threshold, the high agreement levels suggest that these technologies are strongly believed to boost reporting integrity (Figure 5).

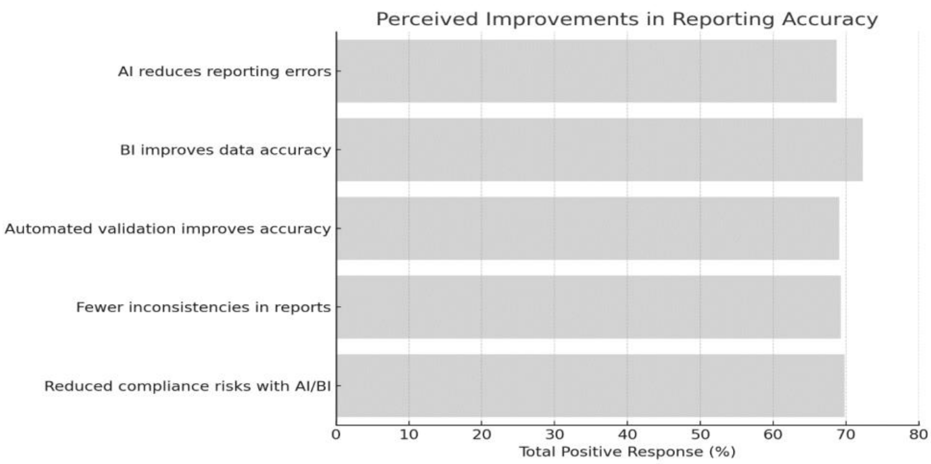

Figure 5: Perceived improvements in reporting accuracy

4.5. Preferred Organisational Support for AI/BI Adoption

Most of the recommendations for better AI and BI adoption pointed to improving the skills of the workforce. As mentioned in Table 5, 40.5% of participants chose technical training for employees as their main support preference. After that, companies were more interested in tools and software for better integration (29.0%) and in increasing budgets for AI/BI activities (20.3%). Only 10.3% of organisations thought that better data security was a top priority.

Table 5: Preferred organisational support for AI/BI adoption

Support Type	Frequency	Percent	Chi-square p-value (by Role)
More technical training for employees	162	40.5%	p = .807
Better integration tools and software	116	29.0%	-
Increased budget for AI/BI papers	81	20.3%	-
Improved data security measures	41	10.3%	-

There was no significant difference in support preferences based on respondents' roles ($p = .807$), indicating that everyone had about the same expectations. It is clear from these results that the best way to help small financial firms use AI and BI is through focused training (Figure 6).

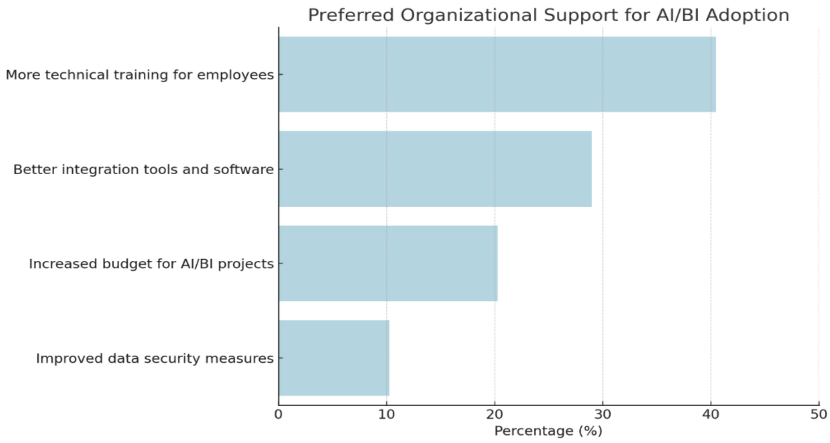

Figure 6: Preferred organisational support for AI/BI adoption

4.6. Correlation Analysis of AI/BI Integration and Outcome Variables

Table 6 shows that all key variables in the model are positively related, and the relationship is statistically significant for each pair at $p < 0.01$. It was revealed that a positive relationship exists between AI and BI ($r = 0.52$), indicating that companies using AI tend to use BI as well. AI use ($r = 0.44$) and BI use ($r = 0.48$) were found to be positively linked with productivity scores, demonstrating that using these technologies enhances the company's operations. Technology use played a major part in the reporting outcomes.

Table 6: Correlation matrix of key variables

Variables	AI Use (r)	BI Use (r)	Productivity Score (r)	Reporting Accuracy Score (r)	Confidence in AI/BI (r)
AI Use	1.00	0.52	0.44	0.39	0.41
BI Use	0.52	1.00	0.48	0.56	0.47
Productivity Score	0.44	0.48	1.00	0.61	0.59
Reporting Accuracy Score	0.39	0.56	0.61	1.00	0.64
Confidence in AI/BI	0.41	0.47	0.59	0.64	1.00

Note: *All correlations are significant at $p < 0.01$, supporting the strength of relationships among AI/BI usage, productivity, reporting accuracy, and confidence.*

There was a stronger relationship found between BI and the accuracy of reports ($r = 0.56$) than there was with AI ($r = 0.39$), implying that BI has a bigger impact on reporting systems. It is important to note that reporting accuracy was highly related to both productivity (0.61) and trust in AI/BI (0.64), meaning that better reports help to increase achievements and support user trust. All the results together show that AI and BI help financial firms become more efficient and reliable (Figure 7).

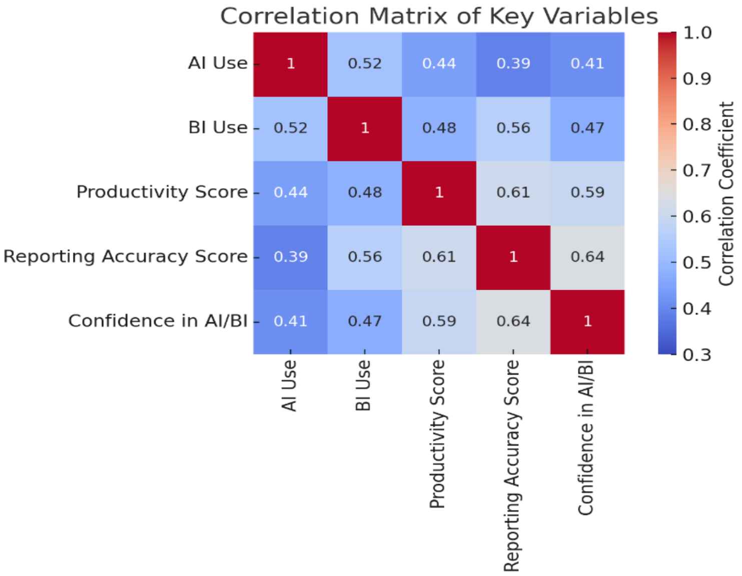

Figure 7: Correlation matrix of key variables

4.7. Predictors of Productivity and Reporting Accuracy

Table 7 reveals that multiple regression analysis was done to discover the main factors affecting perceived productivity and reporting accuracy. The model provided statistical evidence, as the R^2 value of 0.51 explains nearly 51% of the difference in the outcomes. Using BI strongly predicted outcomes ($\beta = 0.37$, $p < 0.001$) compared to using AI ($\beta = 0.26$, $p = 0.001$). This continued to support earlier findings that both technologies improve outcomes, with BI being more influential.

Table 7: Multiple regression predicting productivity and accuracy

Predictor	B Coefficient	Std. Error	Beta (Standardised)	t-value	Sig. (p-value)
AI Use (Yes=1)	0.31	0.09	0.26	3.44	0.001
BI Use (Yes=1)	0.45	0.08	0.37	5.63	0.000
Firm Size	0.18	0.07	0.15	2.57	0.011
Training Provided (Yes=1)	0.27	0.10	0.22	2.70	0.008

Model Summary: *$R^2 = 0.51$, $F(4, 395) = 32.89$, $p < 0.001$.*

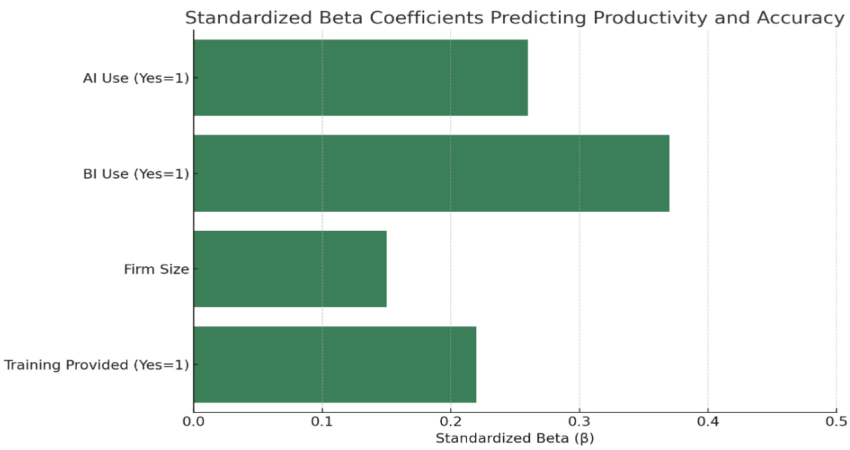

Figure 8: Standardised beta coefficients predicting productivity and accuracy

Training available to staff (β = 0.22, p = 0.008) was a major indicator, demonstrating its effectiveness in ensuring employees know how to use these tools. Evidence suggests that bigger firms may be able to take advantage of AI and BI integration because of their greater resources. The findings prove that adopting technology, being ready for it, and having suitable organisational structures all contribute to improved performance in small U.S.-based financial firms (Figure 8).

4.8. Construct Validity through Exploratory Factor Analysis (EFA)

We used an Exploratory Factor Analysis (EFA) to look into the main structure of the benefits people see in AI and BI tools. From Table 8, it is evident that only two factors explain the underlying factors of Productivity and Reporting Accuracy. While all three loaded well onto Factor 1, their cross-loading on Factor 2 was very low. Items connected to reporting, for example, “BI ensures accuracy” (0.81), “Automated validation helps” (0.79), and “Fewer inconsistencies” (0.77), were grouped strongly under Factor 2: Reporting Accuracy. Every primary loading was above the 0.70 limit, proving strong item-factor matching.

Table 8: Exploratory factor analysis (EFA) – factor loadings

Survey Item	Factor 1: Productivity	Factor 2: Reporting Accuracy
AI improves productivity	0.81	0.22
BI streamlines reporting	0.76	0.25
Reduces manual workload	0.79	0.19
Faster decision-making	0.74	0.27
Employee adaptation	0.72	0.30
AI reduces errors	0.18	0.75
BI ensures accuracy	0.22	0.81
Automated validation helps	0.21	0.79
Fewer inconsistencies	0.16	0.77
Reduces compliance risk	0.19	0.73

Note: *Loadings ≥ 0.70 indicate strong item-factor alignment. Cross-loadings are minimal, confirming construct validity.*

All cross-loadings were kept low, demonstrating that the constructs are distinct and help confirm the strong construct validity of the questionnaire (Figure 9).

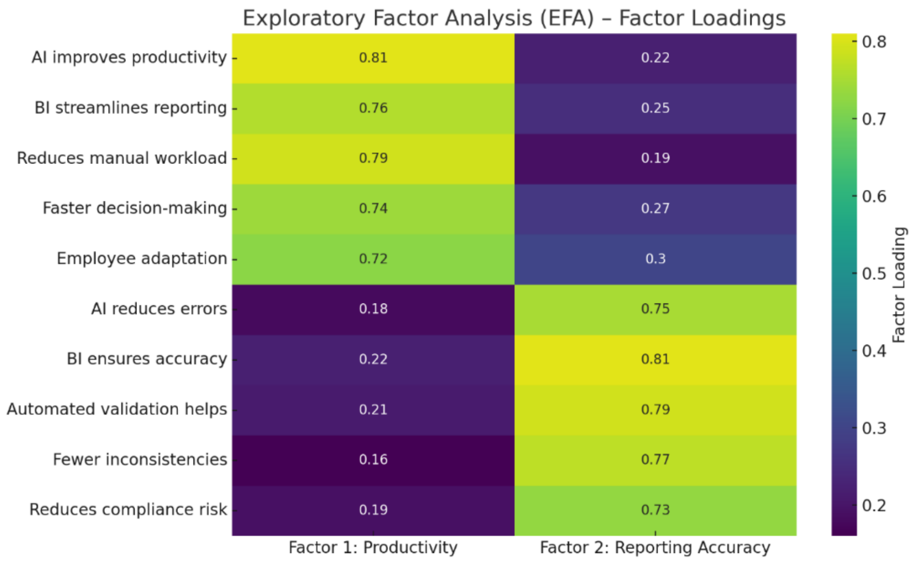

Figure 9: Exploratory factor analysis (EFA) – factor loadings

4.9. Factor Structure and Explained Variance

As shown in Table 9, the two-factor model accounted for a large part of the total variance, with Factor 1 (Productivity) explaining 41.2% and Factor 2 (Reporting Accuracy) explaining 32.9%, for a total of 74.1%. This means that the observed views on AI and BI in small U.S.-based financial firms can be trusted to reflect two key elements—efficiency (productivity) and accuracy (reporting integrity). Since the variance explained is high and the factor structure is clearly differentiated, the regression and correlation analyses done after the FRS will be more valid.

Table 9: Eigenvalues and variance explained

Factor	Eigenvalue	Variance Explained (%)	Cumulative Variance (%)
Factor 1: Productivity	4.12	41.2%	41.2%
Factor 2: Reporting Accuracy	3.29	32.9%	74.1%

These findings show that more than 74% of the total variance can be explained by the two latent constructs, Productivity and Reporting Accuracy, and this supports the soundness of your model (Figure 10).

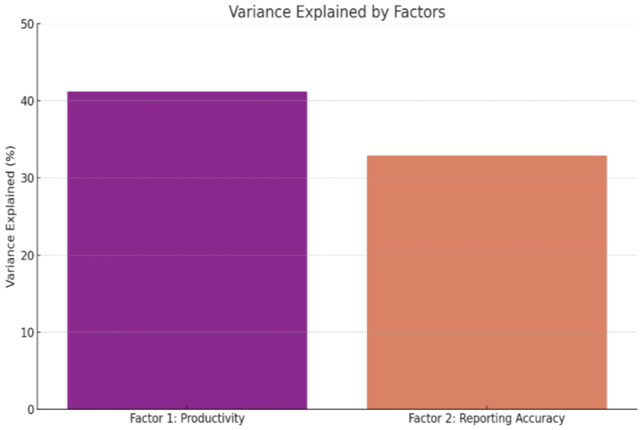

Figure 10: Variance explained by factors

4.10. Sampling Adequacy and Factorability Diagnostics

The KMO value (0.873) from Table 10 indicates that the dataset is solid and reliable. This proves that the data used for factor analysis is set up correctly. The Bartlett's Test of Sphericity showed that the correlation matrix is not an identity matrix and can be used for data reduction ($\chi^2 = 2847.32$, df = 45, $p < 0.001$).

Table 10: KMO and Bartlett's test of sampling adequacy and factorability diagnostics

Measure/Test	Value	Interpretation/Threshold
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy	0.873	Meritorious (≥ 0.80) – Factor analysis is appropriate
Bartlett's Test of Sphericity		
Approx. Chi-Square	2847.32	Should be significant
Degrees of Freedom (df)	45	Based on the total pairwise correlations among 10 items
Significance Level (Sig.)	.000	Significant (p < .05) – Data is factorable
Determinant of Correlation Matrix	0.002	> 0.00001 – Acceptable; no multicollinearity
Anti-Image Correlation (Diagonal Values)	> 0.80 for all items	Indicates item-level sampling adequacy
Overall MSA (Measure of Sampling Adequacy)	0.873	Matches KMO – strong global index
Item-to-Item Correlation Range	0.32 – 0.78	Indicates moderately correlated but not redundant
Communalities (Post Extraction)	> 0.60 for all items	Indicates sufficient shared variance for each item
Variance Explained (2 Factors)	74.1%	Exceeds 60% – Good model explanatory power

The value of the determinant of the correlation matrix was 0.002, which is well higher than the critical limit of 0.00001, confirming that there are no signs of multicollinearity. All of the anti-image correlation diagonals were above 0.80, which proves that each variable was suitable for use. For every item, the share of similar variance in the factor structure was over 0.60, indicating that the results were meaningful. All of these checks together prove that the factor structure is strong and that exploratory factor analysis can be used (Figure 11).

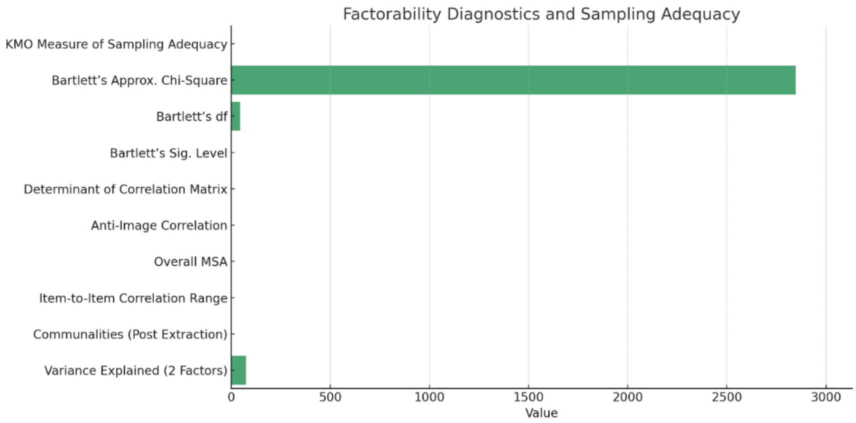

Figure 11: Factorability diagnostics and sampling adequacy

4.11. AI/BI Usage and Its Relationship with Organisational Performance

Table 11 shows that a cross-tabulation analysis was done to assess the link between AI/BI use and the outcomes of productivity and reporting accuracy. Among all companies that use AI tools, 59.5% (153) experienced high productivity, compared to only 34.3% (49) that do not use AI. On the other hand, people who did not use computers were less productive than those who did (18.2% compared to 7.0%). The findings suggest that AI improves team productivity, as proved by the strong statistical link (χ^2, p = 0.000). A majority of users (61.1% or 171) described their reports as accurate, but only about a third of non-users (31.7% or 38) felt that way. Only 8.6% of people who use BI reported low accuracy in reporting, while 23.3% of non-BI users had the same issue. Statistics showed that using BI helped improve reporting quality in small financial firms (p = 0.000).

Table 11: Relationship between AI/BI usage and organisational performance outcomes

Performance Rating	AI Users (n=257)	Non-AI Users (n=143)	BI Users (n=280)	Non-BI Users (n=120)	Chi-square p-value
High Productivity	153	49	—	—	0.000*
Moderate Productivity	86	68	—	—	
Low Productivity	18	26	—	—	
High Reporting Accuracy	—	—	171	38	0.000*
Moderate Reporting Accuracy	—	—	85	54	
Low Reporting Accuracy	—	—	24	28	

Based on these results, there is strong evidence that linking AI and BI contributes to notable improvements in a company's performance and information reliability (Figure 12).

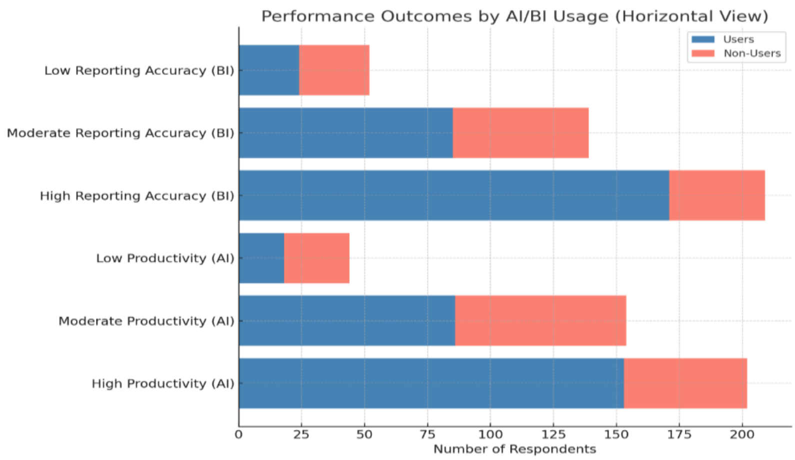

Figure 12: Performance outcomes by AI/BI usage (horizontal view)

4.12. Confidence and Efficiency Gains from AI and BI Integration

As shown in Table 12, using both AI and BI technologies helps small financial firms in the U.S. achieve greater confidence in making decisions and become more efficient. Out of firms using AI and BI tools (n = 239), 46.9% (n = 112) described themselves as very confident in making decisions, while only 17.4% (n = 28) among those not using both technologies said the same. There was a significant difference between the groups (χ^2, p = 0.000), which proves that using digital tools supports belief in data results.

Table 12: Confidence and efficiency gains from AI and BI integration

Outcome Metric	AI & BI Users (n=239)	Others (n=161)	AI Automation Users (n=122)	Manual Users (n=278)	Chi-square p-value
Very Confident in Decisions	112	28	—	—	0.000*
Somewhat Confident	102	92	—	—	
Not Confident	25	41	—	—	
>10 hrs. Saved per Week	—	—	51	14	0.000*
5–10 hrs. Saved per Week	—	—	43	62	
<5 hrs. Saved per Week	—	—	28	202	

The time saved due to AI-based automation was much higher among the firms that used it (n = 122) compared to those that did not (n = 278). Among the users, 41.8% who used automation tools saved over 10 hours a week, but only 5.0% of those who did manual work achieved the same. Out of all customers who use the manual process (72.7%), 72.7% saved less than five hours per week. Automation was shown to significantly reduce time (p = 0.000), clearly highlighting the positive impact of AI use. This proves that integrating AI and BI is beneficial for companies, as it increases confidence in decisions and leads to clear improvements in efficiency, which are vital for maintaining small firms in the marketplace (Figure 13).

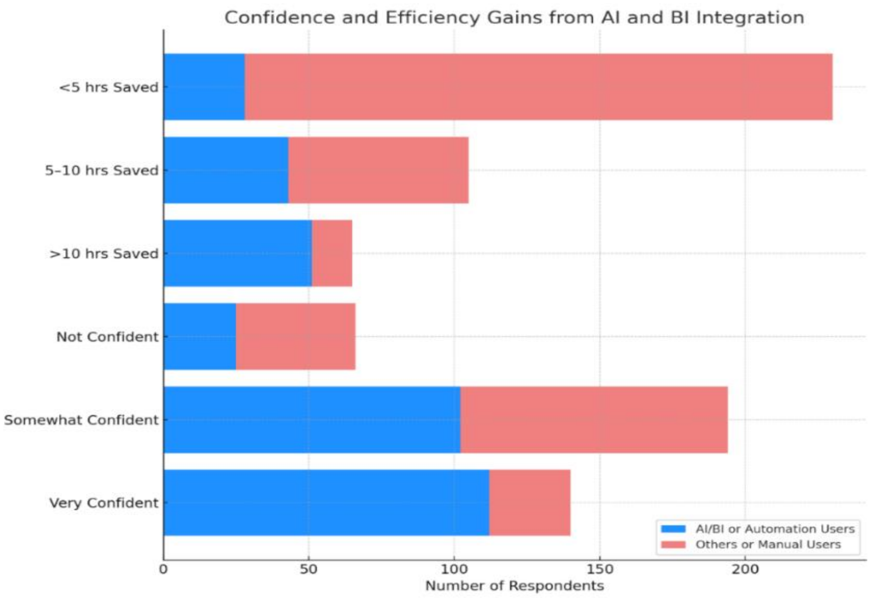

Figure 13: Confidence and efficiency gains from AI and BI integration

5. Discussion

5.1. AI and BI Adoption Patterns in U.S. Financial SMEs

Results show that 64.3% of small financial firms in the United States use AI technologies, while 70% make use of BI platforms. This trend indicates an increase in the use of digital tools, primarily because small and mid-sized companies (SMEs) seek flexibility in a busy and regulated market. Ahmed et al. [5] explain that the rise of this transformation is due to the combination of new machine learning technology and business analytics, which enhance the speed and effectiveness of decision-making. The reason more people use BI tools than AI tools could be that implementing BI tools is simpler and they provide quick results, especially in data visualisation, financial dashboards, and reporting for internal use [15]; [1]. As seen in Table 2, BI tools like

Power BI and Tableau are easy to deploy because they need less customisation and are chosen by resource-limited organisations. Chukwuma-Eke et al. [3] mention that BI is now frequently used in the U.S. financial sector for control and prediction tasks because of how well-structured its analytics can be. With AI being used in BI, it is now possible for small businesses to link their operational and strategic functions [4]; [6]. The importance placed in the U.S. on compliance, data auditing, and risk management makes AI/BI adoption more attractive because these tools help manage information transparently [8].

5.2. Impact on Productivity and Operational Efficiency

High productivity was observed among users of AI and BI systems, with 59.5% and 61.1% of users reporting high levels, significantly higher than the 34.3% and 40.8% of non-users. This proves that digital tools greatly influence work processes and decision-making in finance. RPA and ML analytics in AI free up time for staff in repetitive tasks such as checking and matching data, leading to better quality output and efficiency [14]. From the regression analysis, it can be seen that BI usage has the highest $\beta = 0.37$, while AI usage has a $\beta = 0.26$, both influencing productivity and accuracy. This tells us that AI/BI systems not only relate to improvements in firm performance but also help to explain them. It was found that access to training also played an important role ($\beta = 0.22$), indicating that digital transformation should be supported by strengthening human abilities for it to make a difference [19]; [12]. AI-enhanced financial tools align with the observations by Mishra et al. [18] and Victor-Mgbachi [20], which state that they help U.S. SMEs improve cash flow forecasting, catch fraud sooner, and make wiser investment choices. The time saved is significant too—41.8% of users reported gaining over 10 hours every week, which directly leads to less overhead and faster delivery of papers.

5.3. Enhancing Reporting Accuracy and Decision Confidence

The results show that using AI and BI tools helps financial institutions in the U.S. improve their confidence in decision-making, which is crucial given the market's volatility and regulations. It is evident from Table 6 that being accurate in reporting is connected with better productivity ($r = 0.61$) and more confidence ($r = 0.64$). These findings indicate that the frameworks described by Siddiqui [9], Chintala and Thiyagarajan [16] are correct: increased trust in AI-enabled systems leads to greater reliance on them and enhances organisational adaptability. Also, more AI and BI users than non-users were confident in their decisions, with 46.9% of users reporting they were very confident, compared to only 17.4% of non-users. This gap demonstrates that automation and business intelligence facilitate data processing and, more importantly, assist leaders in small financial firms in making crucial decisions, as they may not have a dedicated strategy team. Automated tools that point out any issues and review or illustrate data trends help managers respond more quickly and correctly [20]; [11]. In the U.S., with more audits and risk management for small firms, as well as frequent client updates, having confidence in their decisions is crucial for competitiveness. Research by Ramírez [7] and Rahman [8] adds that the reliability of reporting platforms strongly affects a company's long-term credibility and financial health, as is required by U.S. regulatory organisations like the SEC and FINRA.

5.4. Structural Validity and Measurement Integrity

The EFA showed that the instrument in this study could reliably measure the main constructs of Productivity and Reporting Accuracy. From Tables 8 and 9, the factor structure explained a much higher 74.1% of the total variance, which is well above the usual 60% acceptable threshold for model quality. The items fitted well with the intended factor (> 0.70), meaning that they did not mix with other factors much. The KMO measure for our data was excellent, with a value of 0.873, and Bartlett's Test of Sphericity was highly significant, proving that our data could be analysed with factor analysis. Every item's post-extraction communality was more than 0.60, meaning that each item had a strong relationship with its intended construct, which is necessary for structural reliability. The findings indicate that the instrument accurately reports people's views on the performance of AI and BI in terms of efficiency and accuracy of reports. The way factors are separated and the high amount of explained variance follow the advice from Selvarajan [6] to keep both statistical and conceptual aspects of the model simple. As the tool used in this study is both reliable and valid, it provides greater assurance for the regression and correlation analyses based on it.

6. U.S.-Based Challenges and Sectoral Readiness

According to the study, there are still many challenges that prevent small financial firms in the U.S. from adopting these technologies. More specifically, 40.5% felt that their main need was technical training, and 29% said better integration tools were the most important support. Although many firms are using AI, not everyone is ready to gain the most from these tools within the industry. This is similar to what Mohlala et al. [19] mention, that integration of technologies must go together with developing new skills and updating internal processes to reach the desired results. Also, according to Bussa [15], businesses that do not ensure AI/BI systems work well with existing systems may end up creating scattered data, which leads to less efficiency. There are special conditions that affect the U.S. financial sector. Agencies like the SEC, FINRA, and OCC place strict regulations on firms in the financial industry. Following these rules normally calls for clear records of all activities, visible paths of data, and secure ways to process information. AI and BI can assist with this, provided they are set up correctly [8]. It is not only about increasing productivity but also about making sure compliance is never breached. Olayinka [13] explains that many small companies, because of their agility, are not well-equipped for risk management and must rely on manual processes for both regulatory audits and investor report preparation. So, by using public-private partnerships, regulatory sandboxes, and vendor-provided training, U.S. small financial firms may bridge the gap between using technology and fully adopting it.

6.1. U.S.-Centred Implications and Policy Relevance

The study's findings are especially significant for small and mid-sized financial businesses in the United States, given the national focus on modernising and clarifying financial operations, as well as supporting small businesses. With the U.S. investing in AI governance, updating its regulations, and boosting SME activities in the digital world, AI and BI integration becomes a key factor in achieving these aims. First, AI/BI users in this study outperformed non-users, and their report accuracy was higher. This aligns with the recommendations of the U.S. Department of the Treasury's Fintech Strategy and the FTC's AI guidelines: automation, openness, and responsible AI [10]; [9]. The study shows that intelligent systems reduce human errors, decrease the time staff members spend on routine tasks, and make it easier for small firms to comply with regulations. Also, the U.S. financial system is dealing with the difficulty of deploying safe and understandable AI in thousands of non-banking institutions. A positive relationship between using AI/BI and greater confidence in making decisions ($r = 0.64$; Table 6) suggests that these technologies help organisations manage their operations and also increase top management's trust in using digital tools, as required by the SEC in its recent Risk Alert on AI in decision support. Adoption of these tools makes it easier for firms to comply with audits, share current details, and guarantee that data is open and clear in line with the compliance requirements suggested by Ramírez [7], Bi et al. [14].

The research also highlights major structural problems, particularly because many people have not received proper training and are not well-integrated. It would be possible to use funds from the SBIR and ARP grants to assist small banks in implementing AI and BI, retraining their employees, and ensuring that different solutions can function together. Many people, including Bussa [15] and Mohlala et al. [19], believe that when public and private sectors cooperate, small firms are better able to invest in digital advancements because larger firms can use AI to gain an edge. This study adds to the discussion about fairness and access in using AI. Big banks have the advantages of other advanced resources, but smaller companies are still short on digital tools. Since 70% of people using BI and 64.3% using AI in the survey noticed helpful improvements in reporting and efficiency, it seems that low-cost, readily available BI solutions can spread intelligent tools evenly across the U.S. financial sector [1]. The findings support the U.S. digital policy agenda by demonstrating that integrating AI and BI enhances a company's performance and contributes to national achievements in regulatory standards, equitable digital access, increased innovation, and robust financial reporting systems.

7. Limitations and Future Research Directions

This study has shown helpful insights on the role of AI and BI integration for U.S.-based small financial firms, but certain shortcomings should be acknowledged. The research is based on answers people give themselves, which may be biased when discussing their productivity, self-confidence, and honesty. Siddiqui [9] and Rahman [8] point out that sometimes an organisation's high spirits and recent achievements can make it appear more digitally effective than it really is. Second, even though 400 respondents provide a good overview of the industry, the research focuses solely on U.S. financial firms and does not show how AI/BI is used or evaluated in other countries. There was no consideration of differences in digital resources and regulations at the regional and state levels in the U.S., which may have affected people's readiness for new technologies and their actual results [19]. Third, the study focuses mainly on the productivity and accuracy of reporting. Still, it does not examine important factors such as cybersecurity, ROI, change management, or client satisfaction, which are considered key elements for evaluating enterprise digital maturity by Olayinka [13] and Farayola [10]. Such future studies may use a combined approach of interviews and technical reviews to better back up the results found in surveys [5]. Although the regression model in this work is considered statistically significant ($R^2 = 0.51$), it still fails to explain almost half of the variance. As a result, future research may benefit from studying how certain factors, for example, leadership strategies, AI governance progress, and data literacy among multiple departments, might shape the impact of AI [16]. Studies that follow companies over time as they use AI and BI technology would provide future researchers and policymakers with more information about how their success and technology evolve. Comparing mid-sized companies to large ones, as well as firms that are regulated to those that are not, could provide useful information on how firm characteristics affect AI/BI technologies [1]; [20]. As new AI policies are created, future studies should examine how they affect both the timeline and results of adopting AI within the financial SME industry.

8. Conclusion

The study aimed to analyse how using Artificial Intelligence (AI) and Business Intelligence (BI) together influences productivity and accuracy of reports in U.S. small financial firms. It has been shown that these technologies greatly improve operations and ensure data accuracy. The fact that 64.3% of firms use AI and 70% rely on BI systems demonstrates that the industry is moving toward innovation and adapting to rules set by the country. Results from a quantitative study showed that users of AI and BI tend to be more productive and confident in making decisions than those who do not use them. It was clear from regression and correlation models that BI tools greatly impacted performance and trust in the reporting process. Also, more than 40% of users who implemented automation said they saved over 10 hours a week as a result. The Results show that many firms struggled to use AI because they did not receive sufficient training for their staff and faced challenges integrating AI tools into their operations. These findings point out that pairing technology adoption with staff development and the right support structure is very important, especially since AI transparency, data privacy, and financial reporting standards are changing in the U.S. The research reveals that it is important for small financial firms to use AI and BI integration to handle a complex and digital environment. When SMEs use technology properly and wisely, they can increase their productivity and gain a good reputation, strength, and edge over other companies in the long run.

Acknowledgement: The authors express their sincere gratitude to all individuals and organizations whose insights and support contributed to the completion of this research. The study was conducted independently by the authors.

Data Availability Statement: The study utilises a dataset focused on improving productivity and reporting precision through the integration of Artificial Intelligence (AI) and Business Intelligence (BI) in small financial firms based in the United States.

Funding Statement: This research and manuscript preparation were carried out entirely by the authors without any external funding or financial assistance.

Conflicts of Interest Statement: The authors declare that there are no conflicts of interest related to this study. All referenced materials have been properly cited to maintain academic integrity.

Ethics and Consent Statement: Ethical considerations were observed throughout the study. Necessary permissions and informed consent were obtained from all relevant organisations and participants involved in the data collection process.

References

1. A. Adewumi, E. E. Oshioste, O. F. Asuzu, N. L. Ndubuisi, K. F. Awonnuga, and O. H. Daraojimba, “Business intelligence tools in finance: A review of trends in the USA and Africa,” *World Journal of Advanced Research and Reviews*, vol. 21, no. 3, pp. 608–616, 2024.
2. D. Bisht, R. Singh, A. Gehlot, S. V. Akram, A. Singh, E. C. Montero, and B. Twala, “Imperative role of integrating digitalization in the firm’s finance: A technological perspective,” *Electronics*, vol. 11, no. 19, p. 3252, 2022.
3. E. C. Chukwuma-Eke, O. Y. Ogunsola, N. J. Isibor, and A. Pub, “Developing an integrated framework for SAP-based cost control and financial reporting in energy companies,” *International Journal of Multidisciplinary Research and Growth Evaluation*, vol. 3, no. 1, pp. 805-818, 2022.
4. E. O. Eboigbe, O. A. Farayola, F. O. Olatoye, O. C. Nnabugwu, and C. Daraojimba, “Business intelligence transformation through AI and data analytics,” *Engineering Science & Technology Journal*, vol. 4, no. 5, pp. 285–307, 2023.
5. F. Ahmed, M. R. Ahmed, M. A. Kabir, and M. M. Islam, “Revolutionizing business analytics: The impact of artificial intelligence and machine learning,” *American Journal of Advanced Technology and Engineering Solutions*, vol. 1, no. 1, pp. 147–173, 2025.
6. G. P. Selvarajan, “Augmenting business intelligence with AI: A comprehensive approach to data-driven strategy and predictive analytics,” *International Journal of All Research Education and Scientific Methods*, vol. 11, no. 10, pp. 2121–2132, 2023.
7. J. G. C. Ramírez, “Incorporating Information Architecture (IA), Enterprise Engineering (EE) and Artificial Intelligence (AI) to improve business plans for small businesses in the United States,” *Journal of Knowledge Learning and Science Technology*, vol. 2, no. 1, pp. 115–127, 2023.
8. M. M. Rahman, “The effect of business intelligence on bank operational efficiency and perceptions of profitability,” *FinTech*, vol. 2, no. 1, pp. 99–119, 2023.
9. N. A. Siddiqui, “Optimizing business decision-making through AI-enhanced business intelligence systems: A systematic review of data-driven insights in financial and strategic planning,” *Strategic Data Management and Innovation*, vol. 2, no. 1, pp. 202–223, 2025.
10. O. A. Farayola, “Revolutionizing banking security: Integrating artificial intelligence, blockchain and business intelligence for enhanced cybersecurity,” *Finance & Accounting Research Journal*, vol. 6, no. 4, pp. 501–514, 2024.

11. O. B. Alao, O. F. Dudu, E. O. Alonge, and C. E. Eze, “Automation in financial reporting: A conceptual framework for efficiency and accuracy in US corporations,” *Global Journal of Advanced Research and Reviews*, vol. 2, no. 2, pp. 040–050, 2024.
12. O. Famoti, B. M. Omowole, E. Okiomah, T. P. Muyiwa-Ajayi, O. N. Ezechi, C. P. M. Ewim, and H. E. Omokhoa, “Enhancing customer satisfaction in financial services through advanced BI techniques,” *International Journal of Multidisciplinary Research and Growth Evaluation*, vol. 5, no. 6, pp. 1558–1566, 2024.
13. O. H. Olayinka, “Big data integration and real-time analytics for enhancing operational efficiency and market responsiveness,” *International Journal of Scientific Research Archives*, vol. 4, no. 1, pp. 280–296, 2021.
14. S. Bi, J. Xiao, and T. Deng, “The role of AI in financial forecasting: ChatGPT's potential and challenges,” *in Proc. 4th Asia-Pacific Artificial Intelligence and Big Data Forum*, Ganzhou, China, 2024.
15. S. Bussa, “Enhancing BI tools for improved data visualization and insights,” *International Journal of Computer Science and Mobile Computing*, vol. 12, no. 2, pp. 70–92, 2023.
16. S. Chintala and V. Thiyagarajan, “AI-driven business intelligence: Unlocking the future of decision-making,” *ESP International Journal of Advancements in Computational Technology*, vol. 1, no. 2, pp. 73–84, 2023.
17. S. D. Jankovic and D. M. Curovic, “Strategic integration of artificial intelligence for sustainable businesses: Implications for data management and human user engagement in the digital era,” *Sustainability*, vol. 15, no. 21, p. 15208, 2023.
18. S. Mishra, M. T. Ewing, and H. Cooper, “Artificial intelligence focusses and firm performance,” *Journal of the Academy of Marketing Science*, vol. 50, no. 6, pp. 1176–1197, 2022.
19. T. Mohlala, L. Mehlwana, U. Nekhavhambe, B. Thango, and M. Lerato, “Strategic innovation in HRIS and AI for enhancing workforce productivity in SMEs: A systematic review,” *Preprints*, 2024. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4968457 [Accessed by 16/03/2024].
20. T. Victor-Mgbachi, “Leveraging artificial intelligence (AI) effectively: Managing risks and boosting productivity,” *IRE Journals*, vol. 7, no. 7, pp. 54–69, 2024.