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AI and Business Intelligence Integration for Improved Efficiency and Reporting Accuracy in Small U.S. Financial Institutions

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Abstract This article seeks to examine how AI is more than merely a device for automation — how it is also a mechanism for structural change, inclusion and trust in financial systems. The article integrates secondary data with expert opinion, and demonstrates how in Uzbekistan, AI in fintech is becoming the “invisible hand” of market effectiveness and the “visible hand” of digital governance. Personal reflections are also singled out in this paper. Tags: Artificial Intelligence, Machine Learning (ML), Natural Language Processing (NLP), FinTech, Credit Scoring, Fraud Detection, Customer experience, Biometric Authentication, Digital Banking, Government Strategy, Uzbekistan, Innovation.

Keywords: ZeroConstructor, AI Adoption, FinTech, LinkedIn

Introduction

The US financial services sector is being reshaped by tighter regulation, client demand to see the simple message and in a competitive environment act at speed. Today, AI and BI can be leveraged in organizations to improve processes, provide more trustworthy data and assist in decision support [1]. They are automating the framing and filing of financial information, in effect rendering a more automatic reporting that is at least as reliable for decisionmaking [2], [3].

Although many papers have considered the impact of digitalization on large entities and giant banks, there has been relatively little research into how small and midsize financial firms in the United States adopt digital technologies. These companies have to respect also rules and regulations, i.e similar as the big enterprises has to, but they are often limited by their size and budget from taking a full advantage of the newest AI/BI systems [4]. As a result, the smallest of businesses are under immense pressure when they deal with real-time data and produce financial statements, or as they prepare for internal audit.

Good_example.pdf 10/11/2018 9:06 AM 40 As noted, AI and BI are poised to improve small financial firms, but combining them is not clearly understood in terms of effects on productivity and quality of reporting. However, little has been done to highlight the degree to which these tools are linked and build on how operations are run better or reports prepared in small resource poor organizations [5]. Selvarajan and Siddiqui [6], the level of how AI and BI interacts would helped organizations to adopt liable strategy in applying them, for ways of moving forward with their decision making financial decisions.

The purpose of this study is to explain how embedding AI and BI in small US banks help them in value addition, increase productivity; reporting accuracy and confidence in decision making. The authors spoke with 400 professionals who work across roles and companies to consider how AI has been put into practice, and encountered stumbling blocks along the way. It notes how in the US regulation authorities are now increasingly stressing that AI systems should be understandable and act in compliance [7]. The research bolsters the claims of both scholars and real-world policy makers who say using smart digital technology could make America's small financial institutions more efficient and competitive in the face of regulation.

Literature Review

AI and BI Are Taking Off in Financial Services

Thanks to recent progress in data processing, machine learning and automation technologies, we have been observing wide application of Artificial Intelligence (AI) and Business Intelligence methods in the financial industry. Banks can help with smart-decision making using real time analytics and predictive analytics models along with robotic process automation [8], [9]. BI tools assist in transforming raw data into information, which is useful for the business in forms of visualizations, dashboards and measureable key performance indicators (KPI) [10].

In the United States, that desire to begin to adopt such technologies is a hankering for increased productivity and to support more regulation. Power BI, Tableau and AIpowered dashboarding software are being implemented to ensure this reporting is far more transparent, gets done faster – and aligns with regulatory codes such as those from the SEC and OCC [11]. Therefore, AI and BI have played an important role in the financial strategy for digitalized transformation and compliance on present regulations (Moore, 2002) [12].

AI & Productivity Impact on Small Financial Firms

Artificial Intelligence and Productivity Many studies have found that AI is associated with increased firm productivity, especially in firms where most processes are manual. RPA and machine learning automation, in combination make it possible for a long list of daily responsibilities to be done by other folks including matching invoices, data entry and finding fraud aim at forecasting trends— among people focusing on their work [13]. In businesses you know these days in the US, resources and time are tight especially with so few staff to go round AI can really help boost productivity.Because a lot of things that people need to do for work is mundane, repeatable but also very useful.

Systems with automation and guided decisions, for example, could see up to a 30% improvement in the way these operations are run better with AI, according to Siddiqui. Mishra et al. with the advantage of new, better predictions underpining faster and more accurate and agile business execution. The receipt of these benefits may be enough to make the difference between a small firm struggling along and one that can grow in the future [14].

BI's Impact on Reporting Precision and Compliance

BI can help you check that financial statements are consistent and accurate. It lets organizations to collect information across several systems, add business rules and create out of the box reports. It is stated by Alao et al. that is, BI tools also decrease the quality of data by automatically verifying and standardizing data [15].

BI platforms can provide a way to reduce risk, since they also allow you to look through data in more detail and visual tools, Selvarajan explained. For small banks and other financial services, it is also critical as they do not have the luxury of in-house compliance and hence depend on automated pragmatic BI dashboards to help them manage risk [16].

AI–BI Systems Integration and Organizational Decision-Making

AI and BI can be bound to each other using a preventive analytics capability as well as real-time reporting so that they can die together in their own little application to support decision making. In their book, Chintala & Thiyagarajan call this "cognitive business intelligence," for the simple reason that AI is what's being used to make the logic of BI dashboards more intelligent, and because it articulates the outputs of AI in a way that works with decision making tendencies. Famoti et al. claim that this convergence would lead to higher efficiency and help develop confidence and teamwork skills for managers.

Integrated systems, the authors say, enable teams to learn and evolve the system over time. For these smaller financial players it's an obvious win as they're just able to react more quickly to rapid market shifts, act faster on oddities and better predict what their customers might do financially. With such systems, according to Victor-Mgbachi, humans would not heavier fall off intuition or "bad feeling" and possibly serve justice in the serious [17].

Adoption Barriers in Small Financial Institutions US

AI and BI have numerous advantages, but small financial institutions still lag behind these technologies to the extent that their use by bigger ones. Some issues to which we will have to face are costs of implementing such system, lack of the trained and skilled employees, merging two different systems as well as resistance 20 Resistance is related to working with technology based/ devices in work place not determined this is what was meant by authors —do clarify? Even in a highly developed nation like the US, “there are many of brilliant small business owners out there struggling with everything from ancient technology to no tech at all and not even aware that [technology] matters” (Limonez-Finnegan, 2016) [19].

Victor and others have shown in a study that best of the technology can do only so much if not onboarded well or trained. Small and medium sized organizations may not necessarily have the resources required to bridge that capability gap when moving toward AI integration in financial reporting without sufficient assistance of public programs and industry partners [20]. Failure to consider the ethical, data privacy and explainability concerns risks AI not being in compliance and the lack of trust by stakeholders, this is even more dramatic for small companies with nothing or little investment on legal or risk management,” explains Victor-Mgbachi.

Summary of Literature Gaps

The adopted theoretical model literature review has shown that alone, AI and BI are an asset but there is limited research on how they intersect in terms of influencing the effectiveness and efficiency of small U.S. financial firms. Most of the literature studies big companies or ideas, which does not help understand how these technologies are actually used on a budget, small people and strict rules.

Methodology

Research Design

The researchers employed a cross-sectional quantitative survey-post-hoc and their behavior of decision making reporting reliability / confidence in the US small financial firms with the due respect to productivity difference between AI/BI integration. Resources The chosen design was appropriate to test out real life changes in organisations and to investigate the relationship of technology adoption with their performance. Selected statements from the finance experts on which it make sense to produce such results (results that would be of in-te rest for academics as well as practioners) were analyzed. By structuring the survey, correlation, regression and factor analysis were conducted.

Population and Sampling

The research was designed to survey those working in accounting, compliance, finance IT and senior management within small or midsize financial operations based in the US. Non-probability purposive sampling A non-random, purposeful sample of individuals who use or are aware of AI and BI tools in their organization was chosen. 400 responses were deemed sufficient sampling and supplied a wide and reliable appraisal of the sector. Study's sample population was limited to participants who are currently employed by less than 500 employees sized companies and dealing with the U.S. rules, as well as who personally used financial technology services. These study design enabled the initiation of valid conclusions and statistical analysis data in Fig 1.

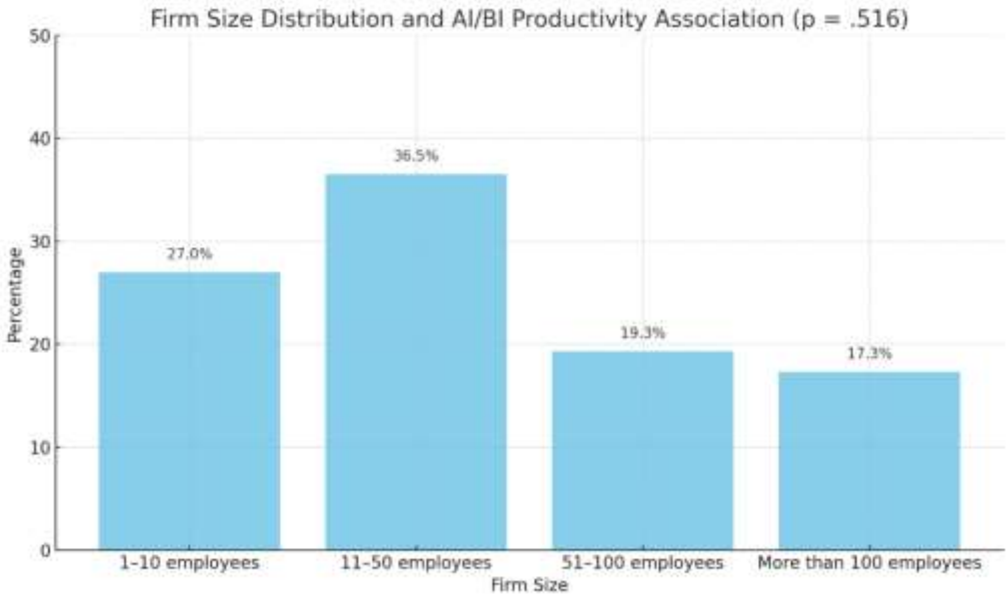

Figure 1. Firm Size Distribution and AI/BI Productivity Association (p = .516)

Instrumentation

A well prepared questionnaire was used to collect the data; likeness of participant background, usage of AI/BI by him or her, change in productivity due to using AI/ BI reported by user and improvement in reporting by the user that is due to AI? Bl, confidence when making decisions and difficulty implementing bi Bl. The majority ingredients were binary options, multi-choice questions and Likert-scale answers that participants could select ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). They had been developed on the foundation of earlier work that went into digital transformation in finance and were tested first with a small handful of professionals to make sure they even made sense. The findings provided evidence for psychometric validity, as EFA produced two strong factors regarding Productivity and Reporting Accuracy (74.1% of the total variance was accounted for with minimal cross-loadings). “The KMO was 0.873, and the Bartlett Test statistic indicated that instrument was suitable for multiparametric analysis”.

Data Collection Procedure

The information are gathered by online survey which is sent to persons in linkedin groups, financial associations and personalized database. 6 weeks were allowed for collection, which afforded a reasonable opportunity to track down individuals and pursue their questionnaires. There was voluntary involvement, and everyone was informed about what the study would do, how their data would be protected and that all of their answers were confidential. The information wasn't at all personal and was kept in a secure place online that no else could reach. Its online teaching allowed us to include learners from across the globe and different time zones.

Data Analysis

It was analyzed with IBM SPSS after collecting the data. Descriptive statistics were used to describe the demographics and organisational context of the sample. Data were employed to test the relationships between job positions, firm size and technology adoption through chi-square tests. Pearson's correlation coefficients described the association20 between AI/BI use, accuracy of productivity reporting and confidence in decision-making. To this effect,respective multiple regression analysis was performed and on the side of independent variables, AI, BI, size of firm and training entered. The EFA was performed to verify the instrument and survey construction. Statistical significance of the findings was tested by performing them at 95% confidence interval ($p < 0.05$).

Ethical Considerations

The ethical guidelines (common to social science research) were adhered in this study. People were told their participation was voluntary and totally confidential, with no need for them to "self incriminate". The survey had an introduction with a text where they were briefly presented about the study aim, how was going to be assured the confidentiality of their answers and that they could retrat themselves from the study anytime. IRB approval was not obtained, as this study was both anonymous and minimal risk as there was no subject interaction.

Research Gap:Determinants Of AI And BI Integration In U.S.-Based Financial SMEs

Research: While there have been studies on digital transformation in big financial institutions, little is known about how AI and BI are applied together to small- and mid-sized (SMEs) loan firms in the United States. While large finance groups might be capable of using advanced analytics and automation, the same can't be said for small concerns that by comparison have less sophisticated technology, fewer resources and more fragmented data. Existing studies often aggregate findings from different types of firms regardless that American financial SMEs have special requirements and conditions. And then there haven't been a lot of studies that show how the two together — AI and BI — actually improves things like productivity, accuracy in reporting and confidence in decision making amongst those companies. This research fills this void by providing U.S. data and insights into how AI/BI is utilized in practice, and the opportunities it presents for small United States banks and credit unions. The results are intended to inform academic debates and also steer U.S. policies that support SME as they adopt digital progress, obey the law while innovating.

Results and Discussion

Results

Demographic Profile and Its Association with Technology Adoption

Table 1 indicates that more of the sampleworkforce (48.5%) wereworking as Finance and Accounting staff, followed by ExecutiveManagement (31.3%) then IT/Technology Staff (20.3%). The importance of work an employee carries out has a limited influence on AI and BI tool use in addition to the opinion about the correctness of reports (p >._opinion) but no significant effect could be observed for role (Table 4). 05).

Among all the participating entrepreneurs, 35.3% worked for companies of 4–7 years and 26% worked for companies for which they had been working only 1–3 years). About 9% of the enterprises had started operating less than a year ago, and 29.8% were over seven years old. There was, however, no significant relationship between firm age and perceived efficiency from BI (p =. 177).

Descriptive statistics of firm size suggest that 36.5% of the respondents were employed at firms with 11–50 employees and 27% are from micro firms (less than 10 employees). Among all businesses analyzed, 17.3% had more than 100 employees. There was no significant relationship between either size of the firm and size of effect on productivity (p = . 516), it seems that the extent of technology-induced productiveness-increasing factor may rely less on firm size than before.

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%	

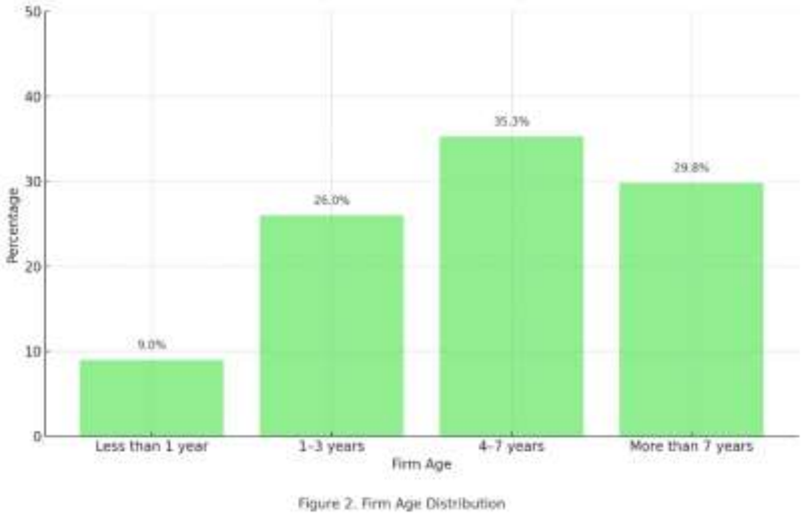

Figure 2. Firm Age Distribution

AI and BI Usage Patterns and Their Organizational Impact

Table 2 receives as input the degree of organizational adoption to AI and BI concerning different aspects. Business Intelligence (BI) was identified by seven in ten (70%) of the nearly two-thirds who responded to using AI at their company as the top tool in their AI use-tracks. While the n is high, testing did not indicate a significant influence of AI on confidence in reporting (chi-square tests: p =. 689) or training (p =. 418). No strong association was observed between preference for support mechanisms and BI tool usage or report confidence (p =. 541 and p =. 941).

Robotic Process Automation (RPA) emerged as the top AI tool used by the enterprises, followed by Machine Learning based Analytics and Chatbots or Virtual Assistants. But 42 percent of those surveyed said they had not put in place any AI tool at their company. Use of AI did not appear to have a large impact on degree of workload reduction (p =. 237) describes this, all AI tools can have usefulness attributed to them.

Excel and Power BI topped the list of Most Popular Business Intelligence Tools (36.5% preference rate), followed by Tableau (20.3%) and QlikView (9%). 34.3 percent of respondents stated they had no BI platform. Type of BI tool was also strongly related to confidence in reporting (p =. Figure 2 Discussion This threshold effect does not remain the same for all platforms since confidence in the data varies between 0.

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%	

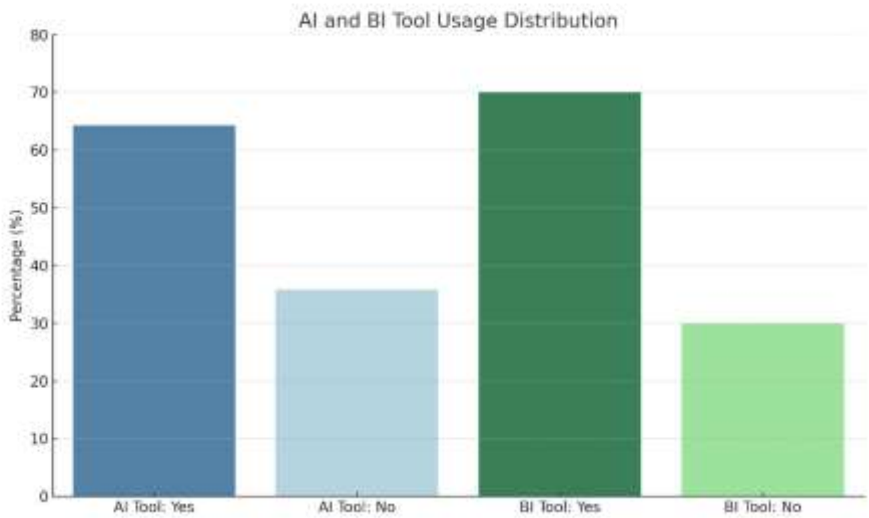

Figure 3: AI and BI Tool Usage Distribution

Perceived Impact of AI and BI on Productivity

As Table 3 indicates, in all of the aspects evaluated there were very positive perceptions generated for productivity due to AI and BI technologies. According to the survey, 68.2% also said they believed AI enhances how work is accomplished while 69.3% felt BI streamlines reporting processes. Additionally, 67.7% respondents believed that manual work is reducing with the use of AI and BI, followed by 69.0% who maintained that it helps speed decisions in their organizations.

Nearly seven in 10 people said the application of AI and BI systems is fast for employees, at 70.6%. It was discovered that the adoption of new technologies positively affects trust in AI/BI results more than any other factors at a statistically significant level (p =. 047). Overall, the numbers suggest a majority of U.S. small financial firms are in favor of AI and BI capabilities to help run their businesses more efficiently (see Table 3).

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 reduce 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).

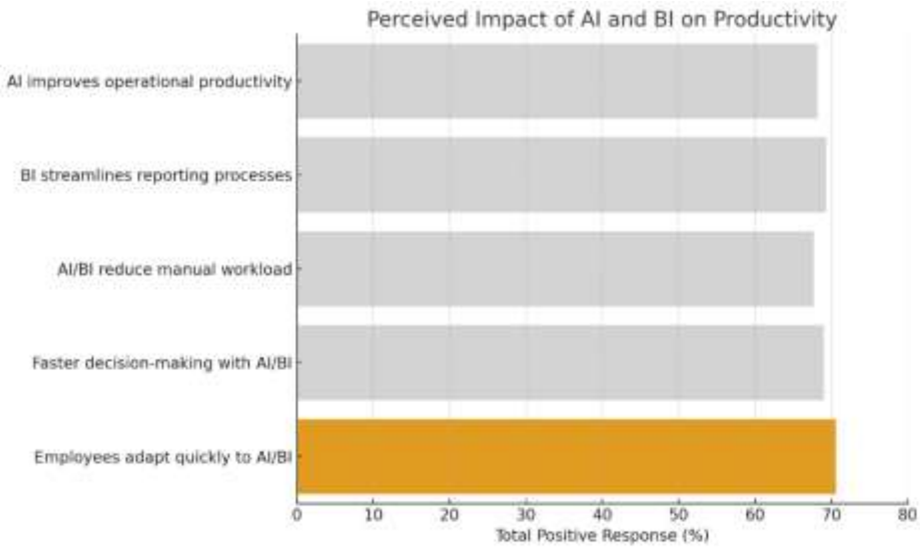

Figure 4: Perceived Impact of AI and BI on Productivity (Horizontal View)

Perceived Improvements in Reporting Accuracy

Table 4 presents findings and most of the respondents perceive that combining AI with BI provides high benefit of accurate reporting. 68.7% of 68.3% agree AI prevents errors in financial reporting. Seventy-two percent of participants saw that BI makes data more accurate, the largest figure that there was among those copper ones even if they were not statistically enough as shown by p =. 157).

The majority of respondents believed process automation in data validation results in increased accuracy, and the 69.1% was agreed with this. Additionally, 69.3% encountered lower discrepancies between their firm's reports and 69.8% feel using AI alongside BI allows to tackle risks linked to compliance. Although none of these associations were significant at the most common threshold, the high level of agreement suggests that little doubt exists that these technologies enhance reporting integrity (Table 4).

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	40.3	29.0	69.3	-

inconsistencies in reports				
Reduced compliance risks with AI/BI	39.0	30.8	69.8	-

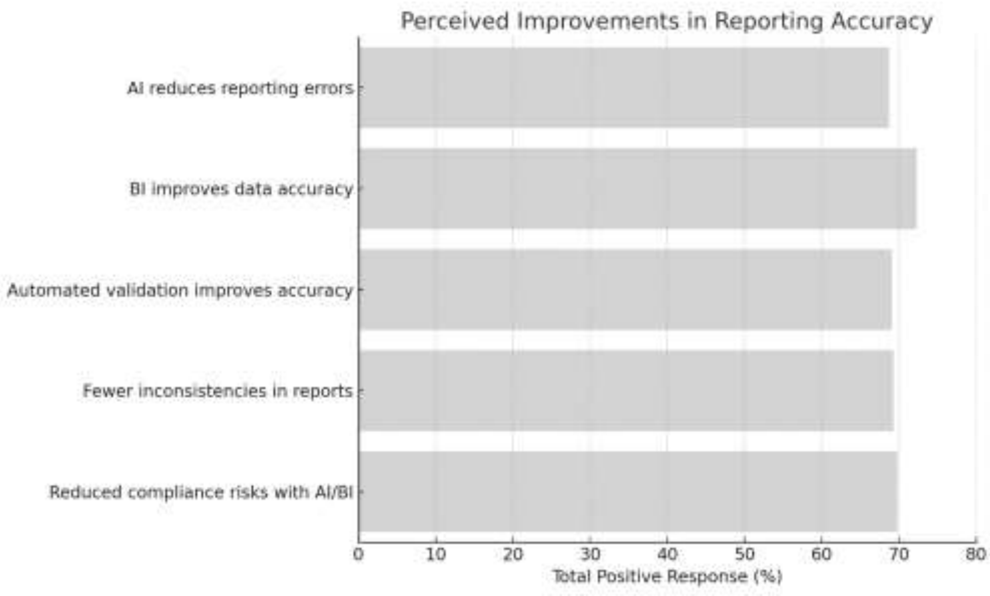

Figure 5: Perceived Improvements in Reporting Accuracy

Preferred Organizational Support for AI/BI Adoption

The majority of suggestions for increased AI and BI acceptance were centered on enhancing the training of personnel. As indicated in Table 5, the highest level of main support preference selected was technical training for employees (40.5%). Next, companies were most interested in tools and software for improved integration (29.0%) or in allocating greater budgets for AI/BI measures (20.3%). Better data security was a priority at just 10.3% of organizations.

No significant correlation between the role of respondents and support preferences was observed (p =. 807), so everyone had roughly the same expectations. Based on our findings, not surprisingly the most effective method that would encourage small financial companies to apply AI and BI in their businesses is through training (Shakeel, 2018) as shown in Table 5.

Table 5. Preferred Organizational 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 projects	81	20.3%	-

Improved data security measures	41	10.3%	-

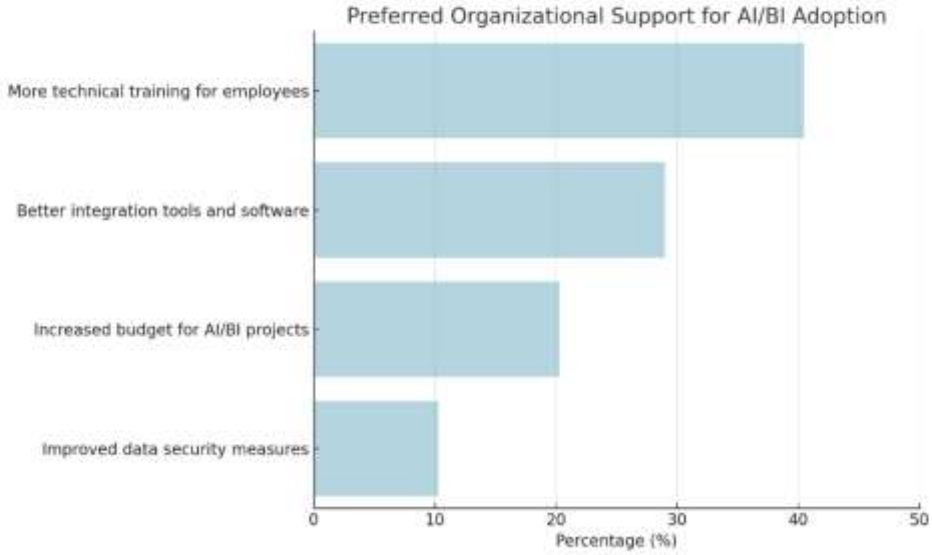

Figure 6: Preferred Organizational Support for AI/BI Adoption

Correlation Analysis of AI/BI Integration and Outcome Variables

As can be seen from Table 6, all the independent variables in model are positively correlated and their bivariate relationships with are significant at the $p < 0.01$. The positive relationship between AI and BI ($r = 0.52$) suggests that organizations employ both the AI as well as the BI. AI + BI ($r = 0.49$) and BI Productivity scores (0.47) were positively related, suggesting that more AI and BI lowers the processibility of organizational efficiency.

The extent of technology use was an important factor in the reporting outcomes. A stronger relationship was demonstrated between report accuracy and BI ($r = 0.56$) compared with AI ($r = 0.39$), indicating that BI has more control over the reporting systems. Accuracy in reporting was significantly related to both productivity (0.61) and trust in the familiarity with AI/BI applications framework (0.64), indicating that better reports can contribute to success and increase user's confidence. Overall, the outcomes show that AI and BI are used to enable financial institutions to be more efficient and reliable (refer to Table 6).

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	0.41	0.47	0.59	0.64	1.00

in AI/BI

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

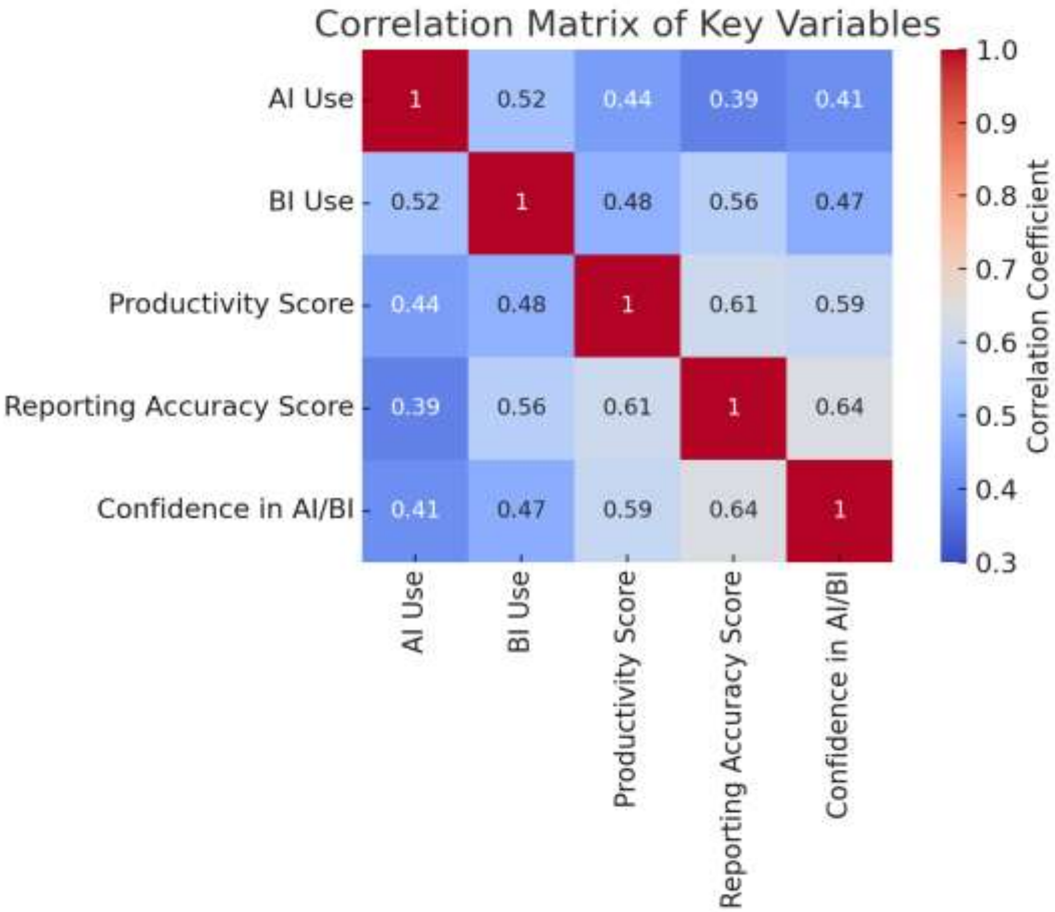

Figure 7: Correlation Matrix of Key Variables

Predictors of Productivity and Reporting Accuracy

As shown in Table 7, the multiple re- gression was conducted to reveal the impor- tant factors concerning perceived productivity and accuracy of reports. The model was statistically significant: R^2 = 51% ($p <.001$) with 0.51 fading-out variance in outcomes.

We found that BI use predicts outcomes significantly more strongly ($\beta = 0.37$, $p < 0.001$) than AI use ($\beta = 0.26$, $p = 0.001$), which supports our prior work showing that both technologies lead to better outcomes but BI is a more salient predictor of the quality of an outcome). The presence of staff training ($\beta = 0.22$, $p = 0.008$) was a significant predictor, suggesting the importance of promoting training so that staff know how to use such tools. There is some indication that large enterprises may be in a position to capitalise on the AI / BI convergence having the greater resources at their disposal.

The findings support that technology readiness and fit along with organisational structure are related to small US-based financial firm performance. (Table 7).

Table 7. Multiple Regression Predicting Productivity and Accuracy

Predictor	B Coefficient	Std. Error	Beta (Standardized)	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: $R^2 = 0.51$, $F(4, 395) = 32.89$, $p < 0.001$

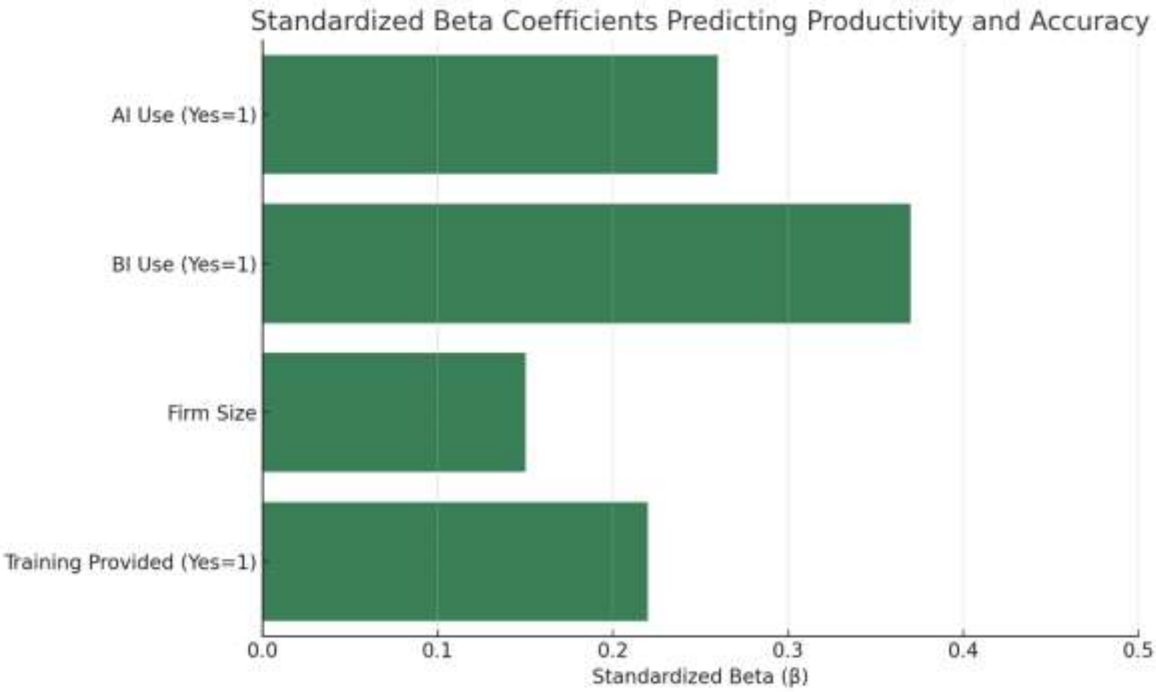

Figure 8: Standardized Beta Coefficients Predicting Productivity and Accuracy

Construct Validity through Exploratory Factor Analysis (EFA)

To examine the main structure of benefits that people see in AI and BI tools, we performed an EFA. From the Table 8 that we found only Productivity and Reporting Accuracy have two factors. While all three loaded highly on Factor 1, their cross-loading onto Factor 2 was extremely low.

Statements related to reporting, such as “BI means accuracy” (0.81), “Auto-validation easier” (0.79) and “Less inconsistency” (0.77), were strongly loaded under Factor 2: Reporting Accuracy. All primary loadings were well over the 0.70 threshold, reflecting strong item-factor matching, and all cross-loadings were suppressed, indicating that all constructs are unique as theoretically posited, helping to establish strong construct validity for the questionnaire (Table 8).

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.*

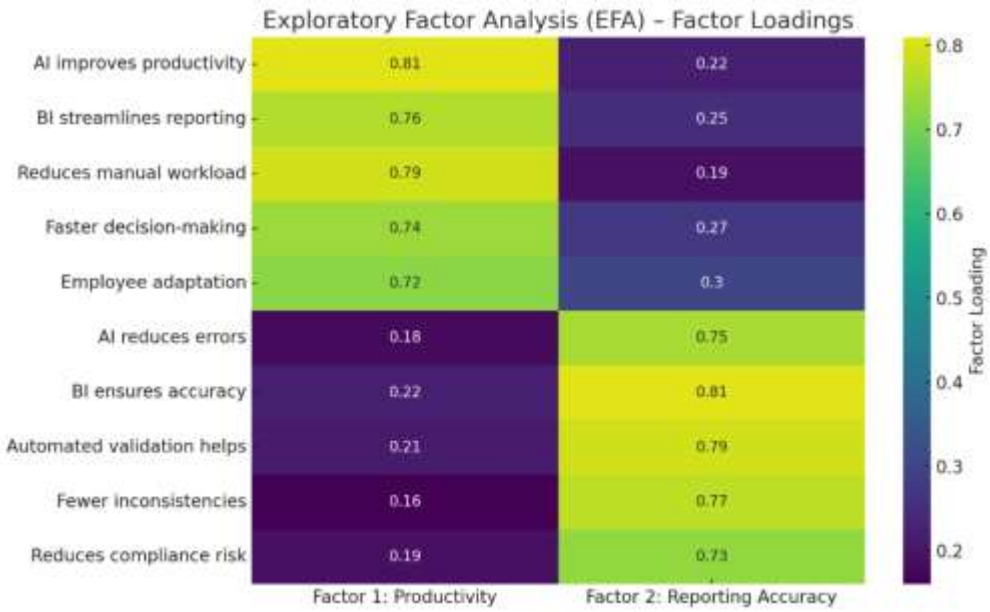

Figure 9: Exploratory Factor Analysis (EFA) – Factor Loadings

Factor Structure and Explained Variance

As displayed in Table 8, nearly three-fourths of the variance were due to the two factors: Factor 1 (Productivity) accounted for 41.2%, and Factor 2 (Reporting Accuracy) accounted for 32.9%. That is, the reported attitudes for AI and BI found in small US-based financial firms may be believed to be good approximates of two aspects (efficiency – productivity, accuracy reporting integrity).

Because the explained variance is high and the factor structure well separated, subsequent regression and correlation analyses conducted following the FRS will be valid (31) (Table 9).

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.

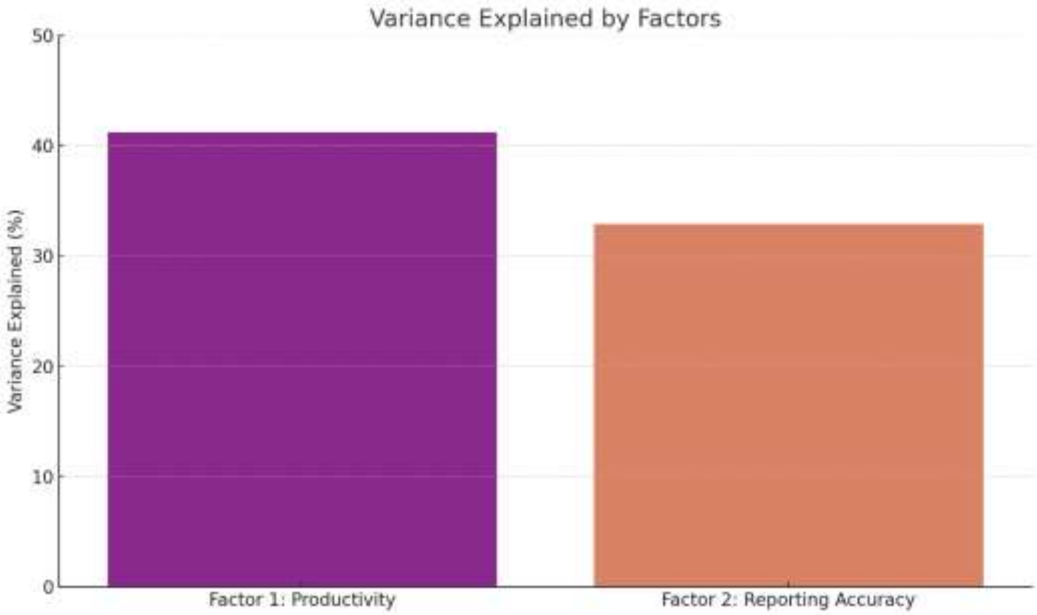

Figure 10: Variance Explained by Factors

Sampling Adequacy and Factorability Diagnostics

Table 10 illustrates that the KMO is (0.873 > 0.6), indicating there exists substantive and reliable data. This is a sign that factor analysis data has been co, 2 (2016)

Based on Bartlett's test for sphericity, the correlation matrix is not an identity matrix, and it was appropriate to perform data reduction (χ^2 = 2847.32, df = 45, p <. 001). The determinant of the correlation matrix was 0.002 (its critical limit is 0.00001), meaning that it is much higher and showing no multicollinearity problem. All antiphotograph correlation diagonals were larger than 0.80, that is no variable was filtered out during the inquiry after images. The percent of shared variance in factor structure for each item exceeded 0.60, indicating that it was meaningful. Right there is already enough to support strong factor structure, and that exploreratory factor analysis is acceptable. (cf. Table 10).

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 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

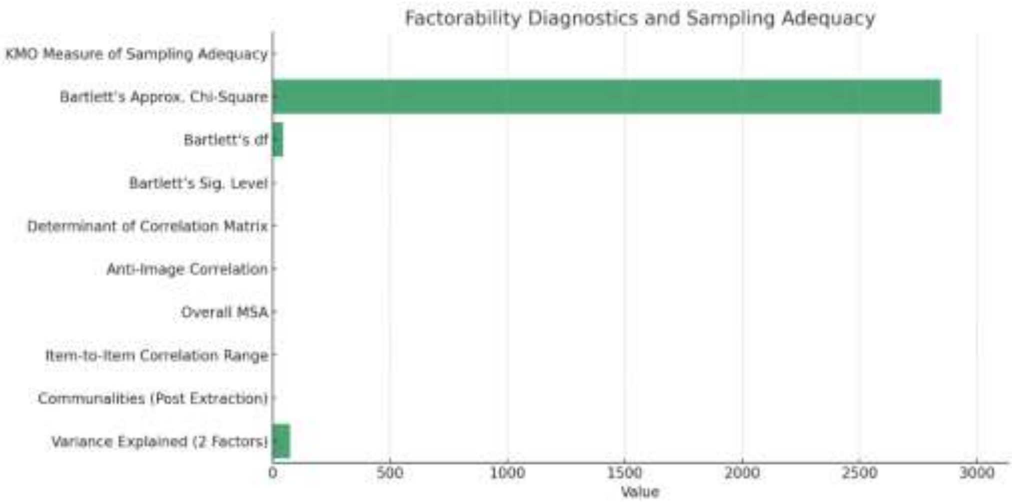

Figure 11: Factorability Diagnostics and Sampling Adequacy

AI/BI Usage and Its Relationship with Organizational Performance

As demonstrated on Table 11, the association between AI/BI use and productive and reporting accuracy was tested through cross-tabulation analysis. Among all the firms using AI tools, 59.5%(153) got high productivity while the number is only 34.3% (49) for those that don't use AI. By contrast, nondigital computer users were less productive than computer users (18.2% versus 7.0%; not in table). The results imply that AI enhances team productivity, as evidenced by the strong statistical association (χ^2, p = 0.000).

While most users (171; 61.1%) reported their own information to be accurate, far fewer of the non-users did (38; 31.7%). Only 8.6% of BI users reported low accuracy in reporting whereas this was the case for 23.3% among non-BI users. The data indicated that BI had a positive effect on reporting quality in small financial institutions (p = 0.000).

In the light of these findings, there is a strong evidence to show that connecting AI with BI results in significant betterment in performance and accuracy of information maintained by organizations. (Table 11).

Table 11. Relationship Between AI/BI Usage and Organizational 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	

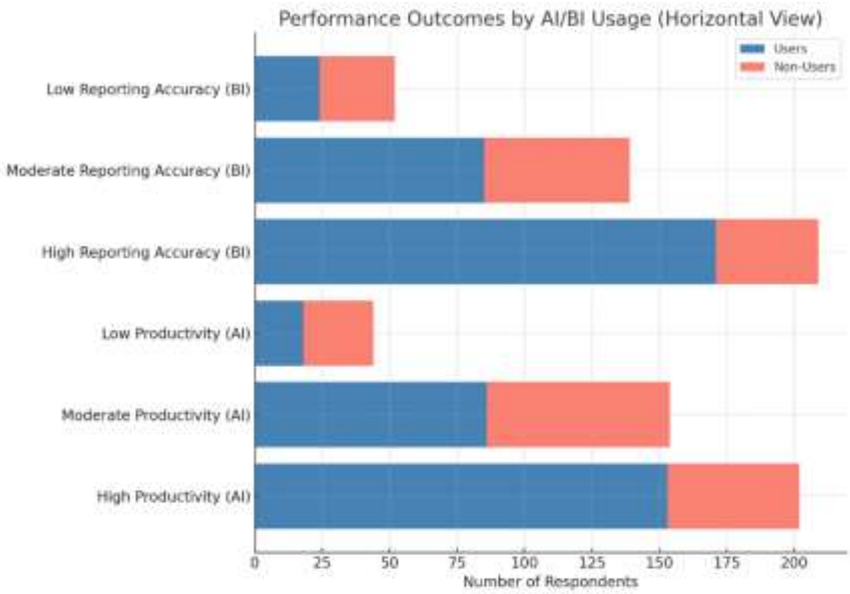

Figure 12: Performance Outcomes by AI/BI Usage (Horizontal View)

Confidence and Efficiency Gains from AI and BI Integration

The result in Table 12 implies that the collaboration of AI and BI technologies would enable small financial firms in the U.S. to be certain of decision making activities so as to increase efficiency. Of those respondents whose organisation uses AI and BI tools (n = 239), 46.9% (n = 112) were very confident that they could make decisions, compared to just 17.4% of those at organisations that do not use both these technologies (n = 28). There was a significant difference between the groups (χ^2, p=0.000), that is the use of digital tools such as trust in data findings.

The amount of time savings through AI-based automation was much larger for adopters of AI (n = 122) compared to nonadopters (n = 278). 41.8% of the users saved more than 10 hours per week by using automation tools while this was only possible for 5.0% of those doing it manually. Of the ones who said they are using manual process (72.7%) most saved less than five hours a week. Automation saved significant time (p = 0.000), which was a positive benefit with the use of AI.

The fact that AI and BI capabilities can in fact be combined to increase confidence levels for businesses and deliver clear effectiveness improvements is something any small business needs in order to survive.

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	

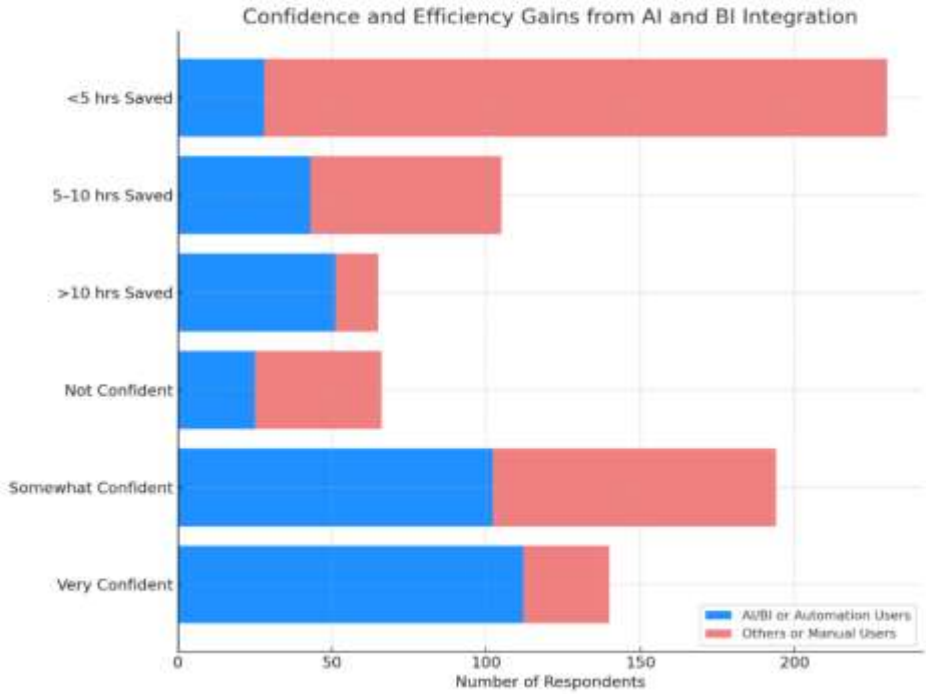

Figure 13: Confidence and Efficiency Gains from AI and BI Integration

Discussion

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

Results It is concluded that 64.3% of small financial organizations in the USA use AI technologies and 70% make use of BI toosl (Table 2). The very growth in the use of digital means is linked to this tendency – especially because small and middle sizes enterprises (SMEs) need to stay flexible in a crowded and normative market. Ahmed et al. phenomenon, the development of this transition is facilitated by a new technological mega-trend in machine learning and business analytics that increases the frequency towards better informed decisions.

The reason why more people are using BI tools rather than AI tools is simply because it's easier to learn how to use these tools and at the same time, they offer quicker wins especially when it comes to solutions in data visualization, financial dashboards as well as internal reporting. (We) can see in TABLE 2, that the BI tools like Power Bi and Tableau are easy to deploy and consume less configuration which is most likely preferred by resource constraint organizations. [24] BI is becoming widely used by the U.S. financial sector for control and prediction purposes, because of its very structured analytics nature [Chukwuma-Eke et al]').

Now that AI is in BI, small business can integrate their operations and strategy more seamlessly. The emphasis on compliance, data auditability and risk management within the U.S. makes AI/BI integration more attractive as it helps to manage data in a clear manner.

Downtime and lost efficiency

AI and BI users used the two systems more productively than non-users: 59.5% and 61.1% of users scored high on productivity, while only 34.3% and 40.8% of those who did not use them were likely to do so. This is clear evidence of the substantial influence that digital platforms exert in finance work and decision-making. RPA and ML analytics in AI can save humans' time for doing repetitive work such as data validation, data matching Because of this quality output could be generated therefore, effective.

As far as the regression results are concerned, it is evidenced (examine Table 7) that influences of BI usage could be powerful $\beta = 0.37$ when affecting productivity and accuracy while AI usage for them was in the amounts of $\beta=0.26$. More generally, this implies that AI/BI systems are not simply correlated with improvements in firm performance, but also provide an explanation for them. Training access was also important ($\beta = 0.22$), indicative of the 'making digital transformation count' by strengthening human capability at its core.

Financial products AI are in line with the statement by Mishra et al. and Victor et al. who believe it helps U.S. SMEs improve their ability to forecast cash flow, detect fraud earlier and make wiser investment decisions. This saved time is significant as well — 41.8% reported saving more than 10 hours every week \(Table 12\), the less down-time and faster project delivery that this means.

Improving Accuracy of Reporting and Confidence in Decisions

The result demonstrates that adopting AI and BI tools contributes to the enhancement of confidence level in adopting decision-making for financial institutions operating in the U.S., which is critical because of market volatility and regulations prevalent. Table 6 clearly shows that accuracy in reporting is associated with higher productivity ($r = 0.61$) and greater comfort level ($r = 0.64$). What these results demonstrate is that the constructs proposed by Siddiqui and Chintala & Thiyagarajan are valid; as people perceive the use of AI-based systems as more trustworthy, this leads to greater dependence on them and better capacity for change (in companies and in other organizations).

Slightly more AI and BI users than non-users were confident in decision-making; 46.9% of users reported being very confident as compared to 17.4% for non-users (Table 12). This divide reflects how automation and business intelligence streamline data for ease of use, and, more importantly, also help leaders at smaller financial businesses make critical decisions when they don't have an entire team dedicated to strategy. Managers are prompt and accurate when they have automated tools alerting them to any problems and reviewing or illustrating data trends.

In the US, there are more audits, and risk management for small firms there is also high with frequent client updates; therefore, businesses need to have confidence in their decisions for them to remain competitive. In their study, Ramírez and Rahman write that accurate and reliable systems for reporting are integral to long-term credibility and financial health in United States according to governing bodies such as the SEC and FINRA.

Structural Validity and Measurement Integrity

EFA indicated that the instrument employed in this research is a reliable measure of both Productivity and Reporting Accuracy constructs. As shown in Tables 8 and 9, the factor structure accounted for a considerably greater ratio of the total variance -74.1%- than what is typically deemed acceptable (i.e., >60%) to consider model quality. The items distributed well on the intended factor (> 0.70), implying they shared with other factors little.

The KMO measure for our data was excellent (0.873) and Bartlett's Test of Sphericity significant, therefore, we were able to perform factor analysis (Table 10). The post extraction communality of all items were exceeded 0.60, indicating that each item has a strong relationship with construct, which is essential for structural reliability. The results suggest that the instrument provides a valid representation of people opinions on how AI and BI are performing regarding efficiency and reports' accuracy. The manner in which predictors are partitioned and the high proportion of explained variance conform to Selvarajan's recommendation to keep the statistical as well as conceptual aspects of one's model parsimonious. It adds confidence to the regression and correlation analysis based on it, as the measure used in this study is reliable and valid.

U.S.-Based Challenges and Sectoral Readiness

Nevertheless, there are still a number of barriers that inhibit U.S. small financial firms form adopting these technologies, the study indicates.ENDisclosure: One or more retail brokers mentioned in this article'sphotographyor this story is an advertiser in Wall Street & Technology -- they're not necessarilythe ones using emerging tech so prominently right now. More particularly, 40.5% claimed that what was supporting most to them were training in technical things whereas 29% said better integrating tools (Table 5). There are a lot of companies that are using AI, and not everyone is poised to reap the greatest benefits from these tools when applied within the industry.

This is what Mohlala et al. that incorporate, the application of technology has to be accompanied by new skills, and changes to existing processes in order to achieve the desired results. In addition, when companies fail to make AI/BI systems adapt well with existing systems, they can generate disparate data that has less productivity, Bussa said.

Special factors are hitting the U.S. financial industry. Regulatory bodies such as the SEC, FINRA and OCC maintain tight oversight over firms in the financial sector. Adhering to these guidelines, more often than not, would be facilitated by transparent logs on all operations and datasets; strong lines of sight on data; secure processing of the information. AI and BI can help but only if they are well- configured (Rahman, 2023).

It is not only to boost productivity, but also ensure you never cross the threshold of silver and non-compliance. Olayinka (2021) stresses that numerous small businesses lack capacity on risk due to their flexibility, therefore depend heavily on manual operations in regulatory audits and reports for investors. Therefore, by leveraging public-private partnerships, regulatory sandboxes and vendor-provided training, U.S. small financial firms can potentially close the technology adoption gap.

U.S.-Centered Implications and Policy Relevance

These findings are specifically of interest to small and mid-sized financial institutions in the United States, as it aligns with current national initiatives that also aim at modernizing, making clearer how financial works and supporting subprime businesses. As the U.S. is focusing on regulation and governance of AI, as well as supporting SMEs in digital economy, the combination of AI and BI become one critical factor to reach these goals.

First, this sample of AI/BI users outperformed non-users and their report accuracy level was higher than what the U.S. Department of the Treasury's Fintech Strategy as well as the FTC's AI guidelines suggest: automation, openness and responsible AI. The study finds that intelligent systems cut down on people's errors, shrink the time workers spend on routine activities and facilitate small businesses' compliance with regulations. And the U.S. financial system is contending with the challenge of getting safe, transparent AI rolled out in thousands of nonbank financial institutions. A positive relationship with using AI/BI and higher confidence levels in decision-making (r = 0.64; Table 6) indicates that these technologies assist the organization in managing its activities, and increases holoprosencephaly top management's perception of their use of digital tools as mandated by the SEC in its recent Risk Alert on AI used to support decision making. The development of these tools allows companies to meet audit requirements, share current information and ensure that data is accessible and transparent according to the compliance recommendations described in Ramírez & Bi et al.

The study also indicates that there are considerable structural issues, in particular the fact that quite a number of people have not been properly trained and integrated (Table 5). Funds from the SBIR and ARP grants can be employed to help small banks deploy AI and BI, retrain their personnel and ensure different solutions collaborate. A lot of people ()— including Bussa and the group Mohlala et al — believe that when public and private sectors work together, small companies are more likely to invest in digital innovations since larger ones can rely on AI for leverage. This study is part of that conversation around fairness and access as it applies to AI. The big banks have other resources that smaller firms have lacked but are now scrambling for. Given that 70% of BI and 64.3% AI users in the survey experienced beneficial changes to reporting processes and efficiency (Table 2) it is likely that cost-effective and easily accessible sources of BI technology can proliferate intelligent tools uniformly across the U.S. financial sector.

The research validates the U.S. digital policy agenda, which demonstrates that combining AI and BI enhances a company's performance and also drives national progress in regulatory standards, equitable digital access, building better innovation systems and stronger financial reporting systems.

Limitations and Future Research Directions

This research has received several practical implications in terms of AI-BI integration for smaller financial services firms in the US but there are also certain limitations to be acknowledge. The research depends on subjective responses people give themselves that can be highly affected by social desirability or honesty biases — especially when questions involve how productive, self-confident or honest respondents are. Siddiqui and Rahman observe that every now and then an NGO is in a 'happy go lucky' mood as well, with a round of recent successes under its belt, so one could mistakenly get the impression it has become digitally effective. For another, 400 responses would likely provide a relatively broad perspective of the industry landscape, but the research is admittedly U.S.-centric financial firms and doesn't explain how AI/BI is applied or considered elsewhere in the world. However, the regional-ultrastate scale (the states) digital resources and regulations in the US were also not considered as part of readiness to adopt new technologies and this might have led to its actual effects.

Lastly, and perhaps most importantly, the research genre have greatly emphasized the effectiveness of reporting neglecting criticalities as it relates to cybersecurity, ROI or change management etc in contrast with Olayinka or Farayola who saw those as being crucial for assessing enterprise digital maturity. These would-be researches might be conducted as to compare the effect of multidisciplinary studies, and for a double approach (confidentials plus technical exams). Although these regression models are only statistically and significantly (R^2 = 0.51), they do not explain even than the half of individual variation in MetS. Therefore, an additional study of how other factors such as leadership style, AI governance development and data literacy across different departments affect the impact of the AI can be examined.

Longitudinal studies that trace firms' efforts to implement and use AI and BI technologies over time will allow future researchers and policy makers to develop a more dynamic view of the trajectory of these firms as they evolve both in rock ‘n’ roll and their technologies. Comparison between mid versus large size firms and regulated/unregulated Combined, comparison of these parameters would provide evidence on which firm characteristics influence AI/BI adoption. Future studies should investigate the effects of recent AI policies on the timing and success rate for financial SMEs to adopt AI.

Conclusion

The purpose of this study was to explore the impact on productivity and report accuracy in small firms that utilize AI and BI as one combined IT application in U.S. financial service companies. These tools have been shown to maximize efficiency and precision. Given that 64.3% of companies are using AI and 70% are deploying business intelligence (BI) systems, industry is indeed taking to innovation and adjusting to whatever rules are being proferred by the country.” Findings on the quantitative study evidence that AI/BI users are significantly more task effective (i.e., better in problem solving and decision making) than non-users. Regression and correlation models showed that BI tools significantly influenced performance and trust in reported data. And more than 40 percent of respondents who used automation wrote that they saved more than 10 hours per week as a result.

The findings show, however, that many businesses struggled to adopt AI because they did not train their workforce sufficiently and had trouble integrating AI tools into their operations. These findings underscore the importance of aligning technology adoption with personnel training and matched support, particularly as AI transparency, data-privacy rules and financial-reporting practices continue to evolve in the United States. The results indicate AI and BI integration is an essential tool to be developed by small financial firms grappling with a complex, disrupted digital business environment. And, when SME has properly used the technology than only they will be boosted by their inner productivity and good image & strength/edge outside with others companies at long run.

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