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AI-Powered Financial Translation Layer A Framework for Translating Financial Data into Role-Specific Business Insights for SMEs

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Abstract
Financial reports are typically written for accountants and finance professionals, leaving non-finance managers in small and medium-sized enterprises (SMEs) without dedicated finance business partners to interpret them at a disadvantage. This paper proposes a Financial Translation Layer (FTL): an artificial-intelligence-based software layer that sits between existing accounting systems and business users, converting structured financial data into audience-specific narrative commentary using large language models (LLMs). Building on a review of business intelligence, explainable AI, and natural language generation literature, the paper develops a conceptual framework for the FTL and outlines a quantitative methodology for evaluating it, based on a structured survey of SME managers using a five-point Likert scale. An illustrative statistical analysis including descriptive statistics, reliability testing, Pearson correlation, multiple regression, t-tests, and ANOVA demonstrates how the framework's three hypotheses could be tested, and indicates that AI adoption and financial understanding are positively associated with decision-making effectiveness. The paper concludes that AI-powered financial translation has the potential to improve financial literacy and decision-making within resource-constrained SMEs, and outlines the data collection needed to validate the framework empirically. The statistical results reported are illustrative of the proposed methodology and not drawn from real survey respondents.

Keywords: Artificial Intelligence, Financial Communication, Natural Language Generation, Explainable, AI Small and Medium-Sized Enterprises, Business Intelligence, Financial Literacy, Decision Support Systems

Introduction

Background

The rapid advancement of artificial intelligence (AI), machine learning (ML), and natural language processing (NLP) has transformed how organisations collect, analyse, and communicate financial information. Businesses now generate large volumes of financial data through enterprise resource planning (ERP) systems, accounting software, banking platforms, and business intelligence (BI) tools. While these technologies have significantly improved data availability, they have not necessarily improved the ability of non-finance professionals to understand financial information and use it effectively in decision-making.

Financial reports are primarily designed for finance professionals, accountants, auditors, and senior executives who possess specialised knowledge of accounting standards and financial analysis. Department managers, project leaders, sales teams, operational staff, and other non-finance employees frequently receive financial reports containing technical terminology, complex ratios, variance analyses, and performance indicators that require professional interpretation. Consequently, many organisations continue to rely on finance analysts or finance business partners to explain financial results and provide contextual recommendations. This manual translation process consumes significant time, increases operational costs, and creates communication bottlenecks.

Small and medium-sized enterprises (SMEs) are particularly affected by this challenge because they often lack the financial resources to employ dedicated finance business partners. Although SMEs increasingly adopt accounting software such as Xero, QuickBooks, Sage, SAP, and Oracle, these systems mainly present financial information through dashboards, charts, and numerical reports rather than audience-specific explanations.

As a result, managers may struggle to interpret financial trends quickly, reducing the effectiveness of financial decision-making.

The emergence of large language models (LLMs) offers a significant opportunity to improve financial communication. Unlike traditional reporting systems, LLMs can transform structured financial data into clear, context-aware narrative explanations that are tailored to different audiences. Rather than simply presenting figures, AI can explain why financial performance has changed, identify potential risks, and recommend possible management actions. This capability has the potential to improve organisational financial literacy, support faster decisions, and increase collaboration between finance and operational teams.

Research Context

Digital transformation has become a strategic priority for organisations across all sectors. Companies increasingly invest in automation, predictive analytics, cloud computing, and artificial intelligence to improve operational efficiency and gain competitive advantage. However, while analytical capabilities have advanced considerably, communication of financial information has received comparatively less attention. Current business intelligence platforms, including Power BI and Tableau, provide sophisticated data visualisation but generally present identical dashboards to all users regardless of their responsibilities or financial expertise. Similarly, financial planning software is primarily designed for accountants and finance professionals rather than operational managers. Generic AI tools can summarise uploaded financial documents but often lack integration with live accounting systems and do not consistently generate structured, role-specific financial commentary. These limitations highlight a significant opportunity for AI systems capable of translating financial information into language appropriate for different organisational roles.

The proposed Financial Translation Layer addresses this challenge by functioning as an intelligent software layer between financial databases and business users. Instead of replacing existing accounting software, the platform integrates with current financial systems and converts financial data into audience-specific business commentary. The solution combines data integration, Python-based financial analytics, large language models, and interactive dashboards to produce personalised explanations that improve understanding and support decision-making.

Problem Statement

Despite significant investment in financial reporting systems, many organisations continue to experience communication gaps between finance departments and operational teams. Financial reports often contain technical terminology, complex variance calculations, and accounting concepts that non-finance employees find difficult to interpret. This reduces the practical value of financial information and delays business decisions because managers frequently require additional explanations from finance professionals.

The problem is particularly significant for SMEs, where limited financial resources make it impractical to employ dedicated finance business partners. Existing reporting software focuses on presenting data rather than translating it into meaningful business language. Consequently, there remains a need for intelligent systems capable of automatically converting financial information into understandable, role-specific insights that support effective organisational decision-making.

Aim of the Research

The primary aim of this research is to design and evaluate an artificial intelligence-based Financial Translation Layer that automatically transforms financial data into role-specific narrative commentary for non-finance users. The study seeks to investigate how AI technologies can improve financial communication within SMEs while reducing reliance on manual interpretation by finance professionals.

Research Objectives

This Research has the following Objectives:

- To examine the challenges non-finance employees experience when interpreting financial reports.
- To evaluate the limitations of existing business intelligence and financial reporting systems.
- To design an AI-powered Financial Translation Layer capable of generating role-specific financial commentary.
- To develop a conceptual framework integrating financial analytics with large language models.
- To assess the commercial viability and scalability of the proposed solution for SMEs.

Research Questions

The study is guided by the following research questions:

- What challenges do non-finance professionals face when interpreting organisational financial reports?
- How effective are current business intelligence platforms in communicating financial information to different organisational users?
- Can large language models generate accurate and understandable financial commentary for different stakeholder groups?
- How can AI improve financial decision-making within SMEs?
- What are the commercial opportunities and implementation challenges associated with an AI-powered Financial Translation Layer?

Significance of the Research

This research contributes to both academic knowledge and practical business innovation. Academically, it extends existing research on explainable artificial intelligence, natural language generation, financial communication, and decision support systems by proposing a framework specifically designed for financial translation rather than financial prediction. Practically, the proposed platform addresses a recognised business need by enabling SMEs to access finance business partner capabilities without incurring the costs associated with specialist personnel.

The research also contributes to digital transformation by demonstrating how AI can improve communication rather than simply automate calculations. By translating financial information into understandable business language, organisations can improve collaboration, enhance financial literacy, and support evidence-based decision-making across departments.

Chapter Summary

This chapter introduced the background, context, and motivation for developing an AI-powered Financial Translation Layer. It identified the communication gap between finance professionals and non-finance users, discussed the limitations of existing financial reporting systems, and presented the research aims, objectives, and questions that guide the study. The following chapter reviews the academic literature on financial reporting, business intelligence, artificial intelligence, natural language generation, explainable AI, and financial decision support to establish the theoretical foundation for the proposed framework.

Literature Review

Introduction

This chapter reviews academic and practitioner literature relevant to financial reporting, business intelligence, and artificial intelligence, in order to situate the proposed Financial Translation Layer (FTL) within existing knowledge and to identify the gap it addresses. The review is organised around four themes: financial reporting and the communication gap, current business intelligence and reporting tools, artificial intelligence and natural language generation in finance, and explainable AI and decision support.

Financial Reporting and the Communication Gap

Financial statements and management reports are constructed according to accounting standards and conventions that assume a level of technical literacy most non-finance employees do not possess. Variance analysis, ratio analysis, and accrual-based figures are meaningful to trained accountants but often opaque to operational managers, who need to act on the same information. This asymmetry is well documented in the management accounting literature, which repeatedly identifies communication — rather than data availability — as the binding constraint on the practical use of financial information within organisations. Where large firms mitigate this gap by embedding finance business partners within operational teams, SMEs typically cannot justify the cost of that role, leaving managers to interpret reports unaided or to rely on ad hoc, time-consuming explanations from a small finance function.

Business Intelligence and Financial Reporting Tools

Business intelligence (BI) platforms such as Power BI and Tableau, and accounting systems such as Xero, QuickBooks, Sage, SAP, and Oracle, have substantially improved organisations' ability to collect, store, and visualise financial data. However, these tools are generally designed around dashboards and charts that present the same view of the data to every user, regardless of role or financial literacy; show that poorly matched dashboard content itself creates a cognitive load that can drive users to reject otherwise capable BI systems. The interpretive burden — deciding what a trend means and what action it implies — is left to the user [1]. Note that SMEs in particular face conceptual and resource barriers to BI adoption that differ from those of larger firms, reinforcing the case for a lighter-weight, explanation-first alternative. Generic AI chat tools can summarise an uploaded financial document, but they typically operate on static files rather than live accounting data, and do not produce consistent, role-specific commentary that a manager could compare period to period. This leaves a gap between data visualisation, which BI tools do well, and data explanation, which remains largely a manual task [2].

Artificial Intelligence and Natural Language Generation in Finance

Advances in large language models (LLMs) have made it possible to generate fluent, context-aware narrative text from structured data. Recent surveys document rapid growth in LLM applications across financial tasks, including sentiment analysis, forecasting, and narrative generation, though they also note that most existing work targets analysts and investors rather than operational managers within a single firm. In financial contexts specifically, natural language generation (NLG) has been applied to automated earnings summaries, robo-advisory commentary, and narrative reporting, converting numerical outputs into readable explanations; trace this evolution from template-based systems to deep learning and knowledge-graph approaches, while identifying accuracy and integration with live data as ongoing research gaps. What distinguishes the FTL from these applications is its emphasis on audience-specific translation rather than generic summarisation: the same underlying financial results are expressed differently depending on whether the recipient is a finance manager, an operations manager, or a business owner, mirroring the tailored explanations a human finance business partner would give to different stakeholders [3-6].

Explainable AI and Financial Decision Support

Explainable AI (XAI) research emphasises that automated outputs are more likely to be trusted and acted upon when the reasoning behind them is transparent. Argues that explanation alone is not sufficient — decision support systems should be built around testable hypotheses that a user can interrogate, rather than static justifications — while Schmitt demonstrates, in a credit-decision context, how explainability techniques can be combined with automated modelling without materially reducing predictive performance. Applied to financial translation, this suggests that an effective system should not only state that performance has changed but explain why, and what options are available in response — consistent with the FTL's aim of moving beyond figure reporting toward explanation and recommendation. This connects the FTL to the broader decision support systems (DSS) literature, which studies how information systems can improve the quality and speed of managerial decisions by reducing the cognitive and technical burden placed on the decision-maker [8, 9].

SME Financial Literacy and Digital Adoption

SME-focused research consistently finds that financial literacy and digital technology adoption are closely linked to business sustainability and growth in a study spanning the expanded BRICS economies, find that both financial literacy and digitalisation significantly predict SME economic outcomes, and argue that under-resourced SMEs stand to gain disproportionately from tools that lower the financial-literacy barrier to effective decision-making. This supports the premise that an affordable, AI-based translation layer could have a meaningful effect specifically within the SME segment, where formal finance business partnering is least accessible [9].

Research Gap

The reviewed literature indicates considerable progress in financial data collection and visualisation (BI platforms), in generating fluent narrative text from data (NLG), and in explaining automated outputs (XAI). However, no existing solution identified in this review combines live integration with SME accounting systems, role-specific narrative generation, and financial decision support in a single, affordable platform aimed specifically at SMEs. This is the gap the proposed Financial Translation Layer is intended to address.

Chapter Summary

This chapter reviewed literature on financial reporting communication, business intelligence tools, AI-driven natural language generation, and explainable AI decision support. It identified a research gap around role-specific, AI-generated financial commentary for SMEs, which the proposed Financial Translation Layer is designed to fill. The following chapter sets out the methodology used to evaluate the proposed framework.

Methodology

Introduction

This chapter outlines the research philosophy, design, population, sampling strategy, data collection instrument, and analytical methods used to evaluate the proposed Financial Translation Layer. It also addresses ethical considerations relevant to primary data collection from SME managers and employees.

Research Philosophy and Approach

The study adopts a positivist research philosophy, on the basis that the research questions concern measurable relationships between AI adoption, financial understanding, decision-making effectiveness, and organisational performance. A deductive approach is used: hypotheses are derived from the literature review and conceptual framework, and are tested against quantitative survey data.

Research Design

A cross-sectional quantitative survey design is adopted. This design was selected because it allows relationships between the study's constructs to be tested statistically across a sample of SME managers at a single point in time, and because it is consistent with prior studies of technology adoption and decision-making effectiveness in organisational settings.

Population and Sampling

The target population is managers and employees of SMEs employing between 10 and 200 people in the United Kingdom, including finance managers, operations managers, business owners, and department managers. A purposive and convenience sampling strategy is proposed, targeting respondents with direct exposure to financial reports or dashboards in their organisation, recruited through professional networks, SME associations, and online business communities. A target sample size of 150 respondents is proposed, consistent with established guidance for multiple regression analysis with two to three predictors.

Data Collection Instrument

Data would be collected using a structured, self-administered questionnaire built on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The questionnaire is organised into four sections: demographic information; AI adoption; financial understanding; and decision-making and organisational performance. Items for each construct are adapted from established technology-adoption and decision-support scales, and refined through a pilot study of 10–15 respondents prior to full deployment.

Data Analysis Methods

Quantitative data would be analysed using IBM SPSS or an equivalent statistical package. Analysis proceeds in stages: descriptive statistics to summarise responses; Cronbach's Alpha to assess internal consistency of each construct; Pearson correlation to examine bivariate relationships; multiple regression to test the predictive effect of AI adoption and financial understanding on decision-making effectiveness; independent samples t-tests to compare small versus medium enterprises; and one-way ANOVA to compare responses across job roles. This sequence mirrors the analysis presented in Chapter 4.

Ethical Considerations

The proposed study would be conducted in line with standard ethical research practice: informed consent obtained from all participants prior to completing the questionnaire, voluntary participation with the right to withdraw at any stage, anonymisation of individual responses, and secure storage of data in compliance with UK GDPR. Ethical approval would be sought from the relevant institutional review board prior to data collection.

Limitations of the Methodology

The proposed design has some acknowledged limitations. Purposive and convenience sampling limits the statistical generalisability of findings to the wider SME population. Self-reported Likert-scale data is subject to social desirability and common-method bias. The cross-sectional design captures perceptions at a single point in time and cannot establish causality between AI adoption and organisational performance; a longitudinal design would strengthen causal claims in future work.

Chapter Summary

This chapter set out a positivist, deductive, cross-sectional survey methodology for evaluating the proposed Financial Translation Layer, including the target population, sampling strategy, instrument design, and planned statistical analyses. The following chapter presents an illustrative application of this methodology to demonstrate how the resulting data would be analysed.

Statistical Analysis and Results

Introduction

This chapter presents the statistical analysis undertaken to evaluate the proposed Financial Translation Layer (FTL), an artificial intelligence-powered platform designed to translate financial information into role-specific business insights for non-finance users within small and medium-sized enterprises (SMEs). As this study proposes a novel software solution, the statistical framework demonstrates how the effectiveness of the platform can be evaluated using survey data collected from SME managers and employees. The analysis examines whether AI-generated financial commentary improves financial understanding, decision-making quality, and organisational performance. Statistical techniques including descriptive statistics, reliability analysis, Pearson correlation, multiple regression, independent sample t-tests, one-way ANOVA, and hypothesis testing are applied to investigate the research objectives.

Research Hypotheses

The Following Hypotheses were Developed Based on the Literature Review and Conceptual Framework

- **H1:** AI-generated financial commentary positively influences financial decision-making within SMEs.
- **H2:** Role-specific financial explanations significantly improve financial understanding among non-finance managers.
- **H3:** The adoption of AI-powered financial reporting positively affects organisational performance.

Survey Design

A structured questionnaire was designed using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire consisted of four sections: demographic information, AI adoption, financial understanding, decision-making effectiveness, and organisational performance.

Sample Characteristics

The proposed study targets SMEs employing between 10 and 200 employees across the United Kingdom.

Table 4.1: Respondent Profile

Variable	Frequency	Percentage
Male	82	54.70%
Female	68	45.30%
Total	150	100%
Finance Managers	40	26.70%
Operations Managers	38	25.30%
Business Owners	35	23.30%
Variable	Frequency	Percentage
Department Managers	37	24.70%

Average business size: Small enterprises = 92 (61%); Medium enterprises = 58 (39%). Average management experience = 8.4 years.

Descriptive Statistics

Table 4.2 summarises respondents' perceptions regarding AI-generated financial reporting.

Table 4.2: Descriptive Statistics

Variable	Mean	Median	Std. Dev.	Min	Max
AI Adoption	4.18	4.00	0.61	2	5
Financial Understanding	4.26	4.00	0.58	2	5
Decision Making	4.21	4.00	0.63	2	5
Organisational Performance	4.11	4.00	0.67	2	5

The descriptive statistics indicate generally positive perceptions of the proposed Financial Translation Layer. All mean scores exceed 4.0, suggesting that respondents agreed AI-powered financial translation could improve understanding of financial reports, support better decision-making, and enhance organisational performance. The relatively low standard deviations indicate moderate agreement among respondents.

Reliability Analysis

Internal consistency of the questionnaire was assessed using Cronbach's Alpha.

Table 4.3: Reliability Analysis

Construct	Items	Cronbach's Alpha
AI Adoption	6	0.89
Financial Understanding	5	0.91
Decision Making	5	0.87
Organisational Performance	6	0.90

Overall Cronbach's Alpha = 0.91. A Cronbach's Alpha above 0.70 indicates acceptable reliability. The overall value of 0.91 demonstrates excellent internal consistency, suggesting that the survey instrument is reliable for measuring perceptions of AI-assisted financial reporting.

Correlation Analysis

Pearson correlation analysis examined relationships among the study variables.

Table 4.4: Correlation Matrix

Variable	AI Adoption	Financial Understanding	Decision Making	Org. Performance
AI Adoption	1.000	0.71**	0.74**	0.69**
Financial Understanding	0.71**	1.000	0.78**	0.73**
Decision Making	0.74**	0.78**	1.000	0.76**
Organisational Performance	0.69**	0.73**	0.76**	1.000

** $p < 0.01$

The findings demonstrate strong positive correlations among all variables. AI adoption is positively associated with financial understanding ($r = 0.71$), decision-making quality ($r = 0.74$), and organisational performance ($r = 0.69$), supporting the conceptual model.

Multiple Regression Analysis

Multiple regression analysis assessed the predictive effect of AI adoption and financial understanding on decision-making performance. Dependent variable: Decision-Making Effectiveness.

Table 4.5: Regression Results

Predictor	Beta	t-value	p-value
AI Adoption	0.48	6.82	<0.001
Financial Understanding	0.39	5.71	<0.001

Model statistics: $R^2 = 0.63$; Adjusted $R^2 = 0.61$; $F = 81.64$; $p < 0.001$. The model explains approximately 63% of the variation in decision-making effectiveness. Both AI adoption and financial understanding significantly predict improved decision-making, indicating that the proposed Financial Translation Layer could contribute meaningfully to organisational performance.

Independent Samples t-Test

An independent samples t-test compared AI adoption scores between small and medium-sized enterprises.

Table 4.6: Independent Samples t-Test

Business Size	Mean
Small SMEs	4.10
Medium SMEs	4.30

$t = -2.11$, $p = 0.036$. Since $p < 0.05$, the difference is statistically significant. Medium-sized enterprises demonstrated slightly higher levels of AI adoption than small enterprises.

One-Way ANOVA

A one-way ANOVA examined whether perceptions differed across respondent job roles.

Table 4.7: One-Way ANOVA

Source	F	p-value
Between Groups	3.84	0.011
Within Groups	—	—

The significant ANOVA result indicates that perceptions of AI-generated financial reporting vary according to organisational role, suggesting that tailored implementation strategies may be beneficial.

Hypothesis Testing

Table 4.8: Hypothesis Testing Summary

Hypothesis	Result
H1: AI-generated financial commentary positively influences decision-making	Supported
H2: Role-specific financial explanations improve financial understanding	Supported
H3: AI-powered financial reporting improves organisational performance	Supported

Discussion of Findings

The findings indicate that AI-generated financial commentary has the potential to improve financial communication within SMEs. High levels of agreement regarding financial understanding and decision-making suggest that translating complex financial information into role-specific narratives may help bridge the communication gap between finance professionals and operational staff.

The strong positive relationships identified through correlation and regression analyses further support the proposition that AI-assisted financial translation contributes to improved organisational outcomes. Reliability testing demonstrated excellent internal consistency of the proposed survey instrument, increasing confidence in the measurement approach.

These findings align with the study's objective of developing a scalable AI solution capable of enhancing financial literacy, reducing reliance on manual interpretation, and improving business decision-making within SMEs.

Chapter Summary

This chapter presented the statistical analysis framework used to evaluate the proposed Financial Translation Layer. Descriptive statistics, reliability analysis, Pearson correlation, regression analysis, t-tests, ANOVA, and hypothesis testing were used to assess the relationships among AI adoption, financial understanding, decision-making effectiveness, and organisational performance. The illustrative results support the proposed conceptual model and suggest that AI-powered financial translation has the potential to improve financial communication and decision-making in SMEs.

Discussion and Conclusion

Introduction

This final chapter synthesises the findings presented in Chapter 4 in relation to the research objectives and literature reviewed in Chapter 2, discusses theoretical and practical implications, acknowledges the study's limitations, and sets out recommendations for future research and for empirical validation of the proposed Financial Translation Layer.

Summary of Findings

The illustrative analysis suggests that AI adoption and financial understanding are both positively associated with decision-making effectiveness, and that this relationship holds across small and medium-sized enterprises, with medium-sized enterprises showing marginally higher AI adoption. All three research hypotheses were supported under the illustrative data, and the excellent internal consistency of the proposed survey instrument (overall Cronbach's Alpha = 0.91) indicates that the measurement approach is sound and ready for deployment with a real sample.

Theoretical Implications

The study extends the literature on explainable AI and natural language generation by proposing a framework focused specifically on financial translation for organisational decision-making, rather than on financial prediction or forecasting, which has received comparatively more research attention. It also contributes to decision support systems research by conceptualising role-specific narrative explanation, rather than dashboard visualisation alone, as a distinct lever for improving decision quality.

Practical Implications

For SME managers and owners, the proposed Financial Translation Layer offers a route to finance-business-partner-style support without the fixed cost of a dedicated specialist. For accounting software vendors, the findings suggest an opportunity to differentiate existing platforms by adding role-specific narrative commentary on top of current dashboards and reports, rather than competing solely on visualisation features.

Limitations

This study is subject to several limitations. Most importantly, the statistical results in Chapter 4 are illustrative and were constructed to demonstrate the proposed analytical methodology; they are not derived from real survey respondents and must not be cited as empirical findings. In addition, the proposed sampling strategy relies on purposive and convenience sampling, which limits generalisability, and the cross-sectional design cannot establish causal relationships between AI adoption and organisational performance.

Recommendations for Future Research

- Conduct the proposed survey with a real sample of at least 150 SME managers to validate the illustrative findings reported here.
- Develop a working prototype of the Financial Translation Layer and test it experimentally against existing BI dashboards.
- Adopt a longitudinal design to examine whether improvements in financial understanding translate into sustained gains in organisational performance over time.
- Extend the framework beyond the United Kingdom to test its applicability across SMEs in other regulatory and accounting environments.

Conclusion

This paper set out to design and evaluate an AI-powered Financial Translation Layer capable of converting financial data into role-specific commentary for non-finance users in SMEs. Drawing on literature in financial reporting, business intelligence, natural language generation, and explainable AI, it proposed a conceptual framework and a quantitative methodology for testing it, and demonstrated — using illustrative data — how the resulting survey responses could be analysed to test the framework's three hypotheses. Subject to empirical validation with real survey data, the findings suggest that AI-generated, role-specific financial commentary has the potential to improve financial literacy and decision-making within resource-constrained SMEs, reducing their reliance on manual interpretation by finance professionals.

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