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Dissertation title: Study on Drivers of LLM Adoption Across Financial Institutions: A Quantitative Approach Using Explainable Machine Learning

1 Abstract

This dissertation will create a data-driven, predictive model to explain the manner and motivations behind Large Language Models (LLMs) being adopted throughout the financial sector. By creating a synthetic dataset of 1,000 rows, this project will investigate how various organisational and technical factors affect the likelihood of LLM adoption. The data will include variables such as institution type, country, AI budget, employee size, technical readiness, cybersecurity level, and governance framework, each selected based on its relevance to academic research and industry reports. Using machine learning models, the study will forecast whether institutions are or are not adopters of LLMs. Output would include an effective predictive model, a ranked list of the most important adoption drivers, and an open, interpretable output to enable decision-making. In addition, the project will also provide visual insights and actionable takeaways tailored to different types of financial institutions to adopt LLMs responsibly and effectively.

2 Background

LLMs have emerged as transformative AI tools that generate human-like text and perform advanced reasoning tasks. Their significance is reflected in the exponential user growth of OpenAI's ChatGPT, which reached 100 million users within two months of launch, marking the fastest adoption rate for any consumer application in history (Paris, 2023). This rapid uptake signals a paradigm shift in how individuals and organisations interact with AI tools.

In the financial industry, LLMs are being tested for a range of tasks like credit scoring, fraud detection, regulatory reporting, and automating customer support. However, even though these tools are becoming increasingly powerful, their use across financial institutions remains inconsistent. Many companies are holding back due to concerns about data privacy, complex regulations, the lack of transparency in how LLMs work, and how well they fit with older legacy systems (EY, 2024; IMF, 2023; McKinsey, 2023). Most of the research so far has focused on how LLMs work and what they can do; however, there is limited understanding of what drives companies to adopt them in the first place. Important factors like the type of institution, their AI budgets, how ready they are technically, and whether they have ethical or governance frameworks are often overlooked (Barclays, 2024; Tao et al., 2025). This dissertation aims to fill that gap by using a structured, data-focused approach. By building a synthetic dataset that reflects different kinds of financial organisations and applying explainable machine learning models like SHAP and LIME, the goal is to uncover and understand the key factors that drive LLM adoption. The outcome will be practical insights that can help companies adopt LLMs in a smarter, more transparent way.

Beyond academic relevance, the inspiration for choosing this topic stems from a genuine curiosity about how a fragile and highly regulated field like finance is navigating one of the most disruptive technologies of our time. Finance deals with sensitive data, high-stakes decisions, and strict regulatory boundaries, making the adoption of AI tools like LLMs both intriguing and complex. While LLMs are gaining popularity across sectors like marketing, education, and technology, it is unclear whether financial institutions are cautiously experimenting or actively deploying these models at scale. This uncertainty led to a deeper exploration of how these institutions balance innovation with governance, compliance, and ethical readiness. The desire to understand this delicate balance and to map out how different types of organisations are adapting motivated the selection of this dissertation topic.

3 Aims and Objectives

This dissertation aims to investigate the organisational, technical, and governance-related factors influencing the adoption of Large Language Models (LLMs) in the financial sector. Using a synthetic dataset and explainable machine learning models, the study will model institutional adoption behaviours and uncover key predictors of readiness and uptake. The overarching goal is to generate transparent, data-backed insights that support responsible and effective LLM implementation across diverse financial organisations.

Objectives:

1. Definition of variables relevant to LLM adoption, including institutional type, technical readiness, governance, and AI investment.

2. Construction of a synthetic dataset simulating 1,000 financial institutions based on a defined variable schema.

3. Exploration and preparation of the dataset through feature engineering, data cleaning, and exploratory data analysis (EDA) to identify patterns, check distributions, and ensure modelling readiness.

4. Development of predictive models (e.g., Logistic Regression, Decision Tree, XGBoost) to estimate LLM adoption likelihood.

5. Evaluation of model performance using metrics such as accuracy, precision, recall, F1 score, and AUC.

6. Application of explainability techniques, including SHAP and LIME, to interpret model decisions.

7. Comparison of adoption trends across institution types, regions, and sizes.

8. Assessment of model interpretability alongside performance to identify the most suitable predictive method.

9. Linking of model findings with ongoing industry discussions on AI ethics, governance, and risk management.

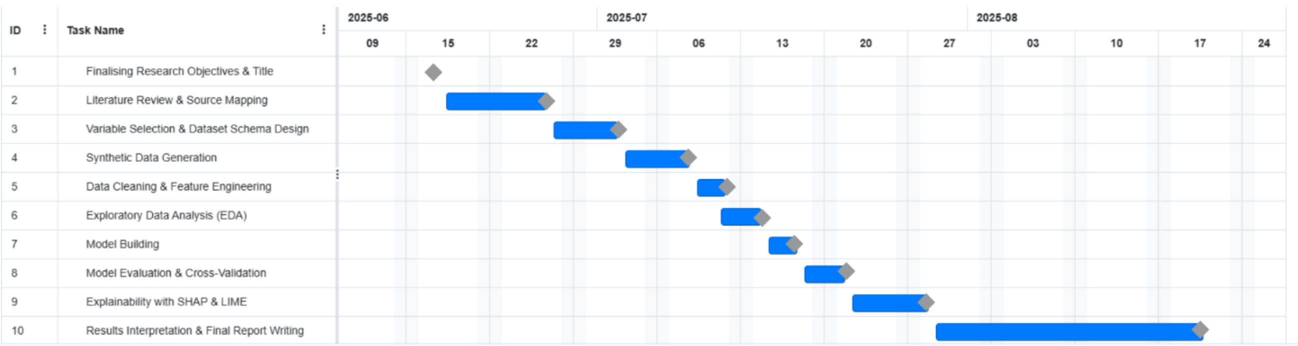
10. Development of practical recommendations for financial institutions and regulators regarding responsible LLM adoption.

4 Approach

This dissertation adopts a quantitative, machine learning–driven approach to investigate the key drivers behind LLM adoption in financial institutions. Each stage of the research process directly supports one or more dissertation objectives, using clearly defined methods for data creation, modelling, and interpretation. The process begins with the systematic definition of relevant variables (Objective 1), selected based on literature and practitioner insights. These variables include technical (e.g., AI budget, technical readiness), organisational (e.g., institution type, employee count), and ethical factors (e.g., governance framework, data privacy compliance). To simulate real-world diversity without breaching confidentiality, a synthetic dataset of 1,000 institutions will be generated using Python (Objective 2). Controlled randomisation techniques will ensure variation across variables, supporting both generalisability and experimental control. Following data generation, the study will perform exploratory data analysis (EDA), feature engineering, and preprocessing (Objective 3). EDA will be used to identify patterns, outliers, and correlations between variables through summary statistics and visualisations (e.g., histograms, boxplots, pair plots). Feature engineering will involve encoding categorical variables, scaling numeric features, and generating derived features that capture interactions between governance and technical readiness. This step ensures the dataset is clean, interpretable, and modelling-ready. The next phase involves the use of supervised machine learning models (Objective 4). Logistic Regression, Decision Tree, and XGBoost will be implemented to predict the binary target variable: LLM_Adoption_Status. These models were selected to represent a range of complexity and interpretability. They will be trained using an 80/20 split and validated using 5-fold cross-validation to ensure performance robustness. For model assessment (Objective 5), metrics such as accuracy, precision, recall, F1 score, and AUC-ROC will be calculated. This multi-metric approach will help detect issues such as class imbalance or overfitting while enabling comparison across algorithms. To ensure the models are interpretable and trustworthy, explainability tools will be integrated (Objective 6). SHAP (SHapley Additive Explanations) will provide both global and local feature importance scores, while LIME (Local Interpretable Model-Agnostic Explanations) will clarify individual predictions. These techniques will make model behaviour transparent and suitable for regulated environments. Subgroup analysis will be conducted (Objective 7) to explore how adoption drivers vary across regions, institution types, and levels of technical maturity. This will ensure that insights are contextual, not one-size-fits-all. The dissertation also compares interpretability versus performance (Objective 8), examining the trade-offs between simpler models and advanced ones like XGBoost. This supports practical deployment decisions. Findings will then be related to ethical considerations and policy relevance (Objective 9), especially in areas such as AI governance, fairness, and compliance. This connects technical output to real-world risk and regulation. Finally, the project will consolidate outcomes into actionable recommendations (Objective 10) to help decision-makers responsibly and strategically adopt LLMs in financial services.

All steps will be conducted in Python using libraries such as pandas, scikit-learn, XGboost, SHAP, and LIME, within Jupyter notebooks to ensure transparency and reproducibility.

5 Plan and Gantt Chart



This dissertation project is structured across 10 tasks spanning from mid-June to late August 2025. The timeline is designed to follow a logical progression from planning and data design to modelling, evaluation, and final reporting. The project begins with finalising the research objectives and title (16–18 June), followed by an in-depth literature review (18–26 June) to establish the theoretical foundation. The next phase involves defining the dataset structure through variable selection and schema design (27 June–2 July), leading to the creation of a synthetic dataset representing 1,000 financial institutions (3–8 July). Once the dataset is generated, it will be cleaned and transformed through feature engineering (9–11 July), followed by exploratory data analysis (11–14 July) to uncover early insights. Model development using Logistic Regression, Decision Tree, and XGBoost will take place from 15–17 July, with evaluation using cross-validation and performance metrics from 18–21 July. Model explainability techniques (SHAP and LIME) will be applied from 22–28 July. Finally, the dissertation concludes with result interpretation and final report writing (29 July–20 August). Key milestones are placed at the end of each task to track progress and guide successful project completion.

6 References

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