Perception of Fraud Risk and Trust in Digital Banking: A Comparative Analysis Among Bbva Bancomer Mexico and Revolut Ireland from Cultural Perspective

MSc Research Project
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Maritza Reyes
Student ID: 23327383

School of Computing
National College of Ireland

Supervisor: Victor del Rosal

National College of Ireland
Project Submission Sheet
School of Computing

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Student ID:	23327383
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AI Acknowledgment

This section acknowledges the AI tools that were utilized in the process of completing this assignment.

Tool Name	Brief Description	Link to tool
ChatGPT	AI tools	https://chat.openai.com/
Grammarly Go	Grammar and punctuation checks	https://www.grammarly.com/grammarlygo

Description of AI Usage

This section provides a more detailed description of how the AI tools were used in the assignment. It includes information about the prompts given to the AI tool, the responses received, and how these responses were utilized or modified in the assignment. One table should be used for each tool used.

ChatGPT
1. ChatGPT
Coding, Handbook

Grammarly Go	
Grammarly Go was used throughout the writing process for checking grammar, punctuation, and readability of the text.	
NA	**NA**

Perception of Fraud Risk and Trust in Digital Banking: A Comparative Analysis Among Bbva Bancomer Mexico and Revolut Ireland from Cultural Perspective

Maritza Reyes
23327383

Abstract

The objective of this research is to observe the perception of trust, risk, and technological acceptance in digital banking within two cultures: Mexico (BBVA Bancomer) and Ireland (Revolut). This study uses the Unified Theory of Acceptance and Use of Technology (UTAUT) to establish its theoretical framework, however it was not applied in its original form, instead, its constructs were adapted and complemented with additional variables to capture the cultural and regional factors influencing fraud risk perception and trust in digital bankingVenkatesh et al. (2012). From a quantitative perspective, a questionnaire was designed to capture variables later reflected in constructs such as performance expectancy (Total Trust in Digital Banking), effort expectancy (Preference for Traditional Banking), and perceived risk through Pearson correlation and Student's t-tests, the analysis shows a very similar results across countries with no statistically significant differences. In addition, a sentiment analysis was performed using 20,000 Revolut reviews and 2,882 BBVA Bancomer reviews were collected through scraping, emotional and rational patterns in the adoption of financial technologies were investigated. Implemented a Traditional models (Logistic Regression, Random Forest, Support Vector Machines) and a Deep Learning Model (Long Short Term Memory) were trained and evaluated, obtaining an average accuracy of 76 (Revolut) and 72 (BBVA) in sentiment classification. The findings contribute that sentiment analysis provides a complement to the more rational perspectives obtained through surveys.

Contents

1 Introduction

1.1 Background

The accelerated digital transformation of the financial sector is redefining the way people use banking services. Digital platforms such as Revolut and BBVA Bancomer have established themselves as leaders in mobile banking innovation. Although BBVA maintains a more traditional identity, it has optimized its digital services over the years, offering users easy access to financial tools and servicesBBVA México (2025). However, the success of these platforms depends not only on their technological capabilities but also on factors such as users' trust in banking services in traditional and digital, risk perception, and ease of use, factors that can vary significantly across cultural and regional contexts. Financial services often face restrictions on technological acceptance due to socioeconomic factors, as well as users' level of digital literacy and trust in institutions. Evaluating these variables becomes even more important when analyzing the experience of users from different cultures. Understanding users' emotional and cognitive responses allows us to identify adoption patterns and challenges that can hinder or foster trust in digital banking.

1.2 Statement of Research Problem

The digital transformation in the financial sector has facilitated the establishment of different digital banking platforms such as Revolut and BBVA Bancomer. The real adoption of these services depends not just on technology, but important factors, from user trust, the perceived risks and banking preference. These perceptions vary considerably with cultural and regional contexts, for instance, between two countries like Mexico and Ireland, which create socioeconomic and digital divides. There exists, however, limited awareness on how these very factors affect acceptance and trust toward digital banking in those cultural contexts. This ignorance stands as an impediment toward designing strategies that would improve the safe and reliable adoption of digital services in diverse markets.

1.3 Study Overview

The research expands our understanding of digital banking acceptance by studying the relationship between trust and risk, as well as technological adoption in FinTech. The adoption of FinTech solutions continues to grow globally, but significant challenges remain regarding technological adoption, especially in sectors where trust and perceived security are determining factors for use, such as digital banking services. The current study aims to analyse the variables that influence the acceptance of digital banking services, comparing Mexico and Ireland. It aims to analyse which factors affect the acceptance of digital banking services from a comparative perspective between these countries. To do so, the UTAUT model was used as a theoretical framework, focusing on three main constructs: performance expectancy (confidence that technology improves performance), effort expectancy (perceived ease of use), and risk perception as an external variable. Through the combined use of structured surveys and sentiment analysis applied to spontaneous reviews, this work seeks to identify the most influential elements in the adoption of and trust in platforms such as Revolut and BBVA Bancomer.

The research seeks to determine how these constructs relate to each other in different cultural contexts and what implications they have for the design, communication, and improvement of digital financial services in emerging and developed markets. To provide an understanding of these variable constructions, the unified theory of acceptance and use of technology (UTAUT) model and sentiment analysis will be integrated. Hence, this study is structured as 3 follows: section 2 examines the existing literature; Section 3 describes the methodology: Section 4 explains the Design, 5 Implementation, 6 Evaluation and Discussion, 7 and lastly Conclusion and future work.

1.4 Research Objectives

- Analyse users' preference for traditional and digital banking.
- Evaluate the perceived risk associated with digital services in Mexico and Ireland.
- Identify cultural differences impacting trust, preference, and risk perception toward digital banking.

1.5 Research question

How do cultural and regional differences influence the perception of fraud risk and trust in digital banking among users of BBVA Bancomer Mexico and Revolut Ireland?

1.6 Research Hypothesis

1.6.1 Hypothesis

Total trust in digital banks (Performance Expectancy) This construct represents users' perceptions of security, transparency, and rapid response from digital banking platforms. The construct consists of questions 9, 14, and 15 in the questionnaire.

H1

- There is no significant relationship between total trust in digital banking (Q9, Q14, Q15) and the intention to use digital banking services.
- There is a significant relationship between total trust in digital banking (Q9, Q14, Q15) and the intention to use digital banking services.

Risk Perception (Additional Construct) This construct incorporates perceptions of digital insecurity, which include concerns about fraud and cyberattacks, as well as technological vulnerabilities. The construct is established through questions 5, 6, and 13. Although perceived risk is not part of the original UTAUT model, previous studies have included it as an important factor moderating the adoption of financial technologies.

H2

- There is no significant relationship between risk perception (Q5, Q6, Q13) and the intention to use digital banking.
- There is a significant relationship between risk perception (Q5, Q6, Q13) and the intention to use digital banking.

Preference for traditional banking (Effort Expectancy / Facilitating Conditions) This factor reflects resistance to digital tools through a preference for human or face-to-face interactions. Questions 17, 10, and 16 are part of this assessment, which show a low expectation of digital effort or improved conditions in traditional channels.

H3

- There is no significant relationship between preference for traditional banking (Q10, Q16, Q17) and the intention to use digital platforms.
- There is a significant relationship between preference for traditional banking (Q10, Q16, Q17) and the intention to use digital platforms.

2 Related Work

Digitalization in the financial sector has driven the growth of services such as mobile banking and Fintech platforms, generating increased interest in studying the factors that determine their adoption. A systematic review of 25 academic studies on digital banking was conducted through analysis of user experience, risk perception, digital culture, regulation, and methodological evaluation. This review helps identify common patterns, tensions among innovation and security, and the need to adapt theoretical models to specific cultural contexts.

2.1 User Trust and Digital Banking Experience

User trust is the fundamental element in the adoption of digital banking services. According to Musyaffi et al. (2024), they argue that initial trust is formed from the perception of security in conjunction with institutional reputation and interface, while models such as TAM and UTAUT2 emphasize the influence of ease of use, perceived usefulness, habits, and cost-benefit, analysed by variables such as age and gender Venkatesh et al. (2012). Jafri et al. (2024)demonstrates that previous controversies in the FinTech sector generate scepticism, but a systematic review confirms that perceived security, privacy, and institutional integrity are key to fostering trust. Choudhuri et al. (2024), highlights the understanding of security policies as a determining factor, while Shehzadi (2023) emphasizes system stability and customer service. Martínez-Navalón et al. (2023) and Amorelius (2024) agree that institutional transparency and user experience are determining factors, although the latter shows how cultural values influence the perception of trust. In Mexico, Mansumitrchai and Al-Malkawi (2011) emphasize the role of technological familiarity and service culture, and Gupta and Gupta and Shukla (2024) point out the importance of legal frameworks. Finally, Aldboush and Ferdous (2023) propose that trust in FinTech requires ethical management of big data and an active commitment to privacy.

2.2 Security, Digital Fraud and Risk Awareness

Perceived risk is a determining factor in the relationship between users and digital financial platforms Sahani et al. (2023). Users experiencing digital threats show greater insecurity, which impedes their adoption of digital services. Waliullah et al. (2025) shows that the implementation of advanced technologies such as biometric authentication or encryption requires users to understand how they work.

Personal perception of vulnerability represents a fundamental obstacle for users with low levels of digital literacy. Laurent and Sinz (2019) demonstrated through testing that the perception of cybersecurity and organizational trust directly affect the intention to use FinTech services. Their UTAUT model reveals that the perception of protection depends not only on the technology implemented, but also on trust in the institution that offers it, meanwhile, Avila (2007) shows that the implementation of technical measures in Mexico without educational support caused people to reject these measures and perceive insecurity. This reinforces the need for integrated technological protection strategies and user training.

2.3 National Culture and risk Behaviors

Digital banking risk perception depends strongly on cultural elements. According to Gerlach and Eriksson (2021) financial user behaviour gets influenced by uncertainty avoidance and individualism dimensions. People in Mexican collectivist societies depend more on trusted social networks which decreases their risk perception through community support Eljilany et al. (2023). Research shows that Thai users adopt mobile banking services more easily than Americans because they follow stronger social norms Lonkani et al. (2020). The Mexican culture of high uncertainty avoidance results in reduced adoption of digital services which customers view as complicated or insecure Moreno-García (2023). According to Rababa and Ali's research nationalistic attitudes toward technology and lack of trust in institutions decrease technology adoption Rababa and Ali (n.d.). European users trust digital platforms such as Revolut because these systems use biometric technologies and artificial intelligence along with virtual cards and fraud education which strengthens user control and security perception Revolut Group Holdings Ltd (2023). The way culture shapes risk attitudes and technological solution acceptance demonstrates clear differences between user groups. The cultural background of a nation determines how its users view the dangers linked to digital banking services. The acceptance and rejection of technologies together with financial system trust requires cultural understanding beyond technical and economic perspectives. The analysis of user differences between Mexican and European customers regarding their BBVA Bancomer and Revolut platform experiences depends on this essential viewpoint.

2.4 Regulation, institutional Ethics and Digital Governance

The successful implementation of open banking depends essentially on proper regulation coupled with good digital governance. Martín et al. (2016) indicate that the Open Banking Standard establishes fundamental principles to achieve ethical governance in digital environments based on transparency, security, and user control. The correct application of these principles depends on the different institutional systems of each nation. Alonso-Robisco et al. (2025) investigate how Spanish regulations have affected the evolution of fintech, showing discrepancies between innovation and the need to comply with regulations. Competition is restricted by overly strict regulation, but overly flexible regulation increases the dangers of systemic risks. Polasik et al. (2024) present a data-driven approach to the European perspective, showing progress in interoperability and data protection but warning about regulatory fragmentation and cross-border supervisory challenges.

Feyen et al. (2021) emphasize that the financial digital transformation must receive an inclusive and adaptive public policy. Governance must incorporate sustainability alongside equity and algorithmic accountability as fundamental elements for artificial intelligence in financial decisions.

2.5 Quantitative Methodological Approach for the Analysis of digital Perception and Trust

The study of digital banking perception and trust needs a measurement framework that integrates user rational and emotional elements. This research adopts a quantitative method approach which combines technology adoption theory with sentiment analysis to study the phenomena through multiple perspectives. The analysis utilizes the UTAUT2 framework established by Venkatesh et al. (2012) as its foundation since it explains technological acceptance through expected effort and perceived benefits and habitual use and facilitating conditions. The theoretical framework from this model provides essential structure to analyse user behaviour patterns. The analysis incorporates artificial intelligence as a supplementary method to study both subjective and emotional content. Multiple research studies have shown that Long Short Term Machines (LSTM) neural networks Atmaja et al. (2023) together with Logistic Regression (LR) Random Forest (RF) and Support Vector Machines (SVM) effectively analyse financial contexts where unstructured opinions help identify patterns beyond structured questionnaires Cicekyurt and Bakal (2025)Bhowmik et al. (2025)

3 Methodology

3.1 Research Design

This study uses a quantitative research methodology to combine statistical information with spontaneous data to assess the perception of digital banking trust through a comparative cultural analysis. The research focuses on two distinct regions with distinct socio-technological characteristics: Mexico, represented by the BBVA Bancomer platform, and Revolut Ireland. The design uses the UTAUT model, which was adapted to identify variables of institutional trust, risk perception, and preference for traditional or digital channels. The instruments and interpretive analysis were based on this model for structuring.

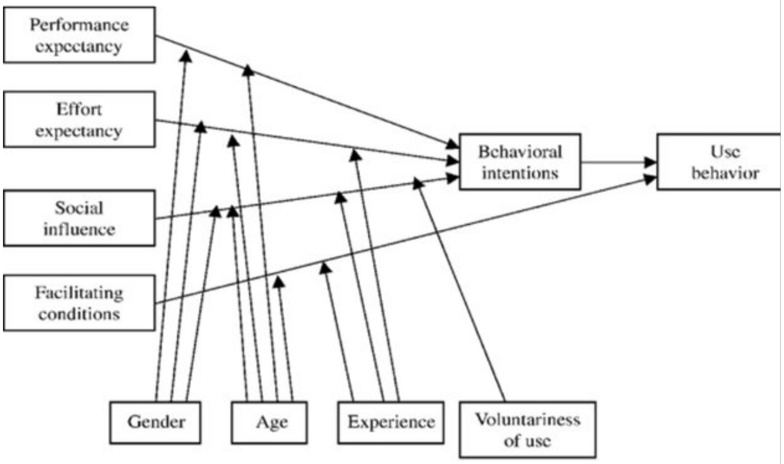
3.2 Proposed models

The structured questionnaire was utilized Venkatesh's UTAUT model as its foundational base for design Venkatesh et al. (2012). The research applied an adaptation of the traditional model to study only the perception of trust in digital banking. The survey focused on digital and traditional banking, using as an examples like BBVA Bancomer and Revolut, and the questions were organized into three main constructs based on the adaptation made.

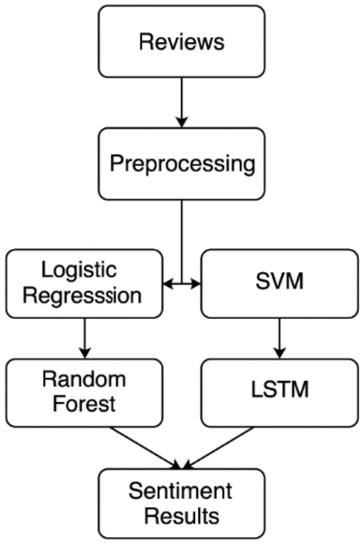
- Total trust in digital banks (Performance Expectancy) assesses how users perceive digital services as safe, effective, and transparent.
- Perceived risk (an external construct included due to its relevance) covers concerns about cyberattacks, data loss, and fraud that decrease technological adoption.

- Traditional banking preferences (Effort Expectancy / Facilitating Conditions) represents the resistance to using digital channels and the preference for human or face-to-face attention.

Sentiment analysis was performed by applying LSTM neural networks and traditional models (LR, RF, SVM) to real user reviews of BBVA and Revolut collected from the Google Play App Store, which have proven effective in financial analysis according to Cicekyurt and Bakal (2025) and in predictive sentiment analysis in crypto markets by Bhowmik et al. (2025). The analytical methods allow for the discovery of genuine emotions, which strengthen the questionnaire results to achieve a complete understanding of the phenomenon studied.



(a) Venkatesh's UTAUT model



(b) Pipeline

Figure 1: Model and Pipeline

The specific phases were data collection, preparation, and analysis are detailed in the following sections.

3.3 Data Collection

A bilingual (English-Spanish) digital questionnaire was designed for distribution on social media (Instagram, Facebook, and WhatsApp) from June 6 to 15, 2025. Sixty-one valid responses were collected, ranging in age from 21 to 55+ years, using 5-point Likert-type scales, with questions about trust in digital banking, risk perception, preference for traditional channels, and sociodemographic data (age, country, frequency of use). Additionally, 20,000 reviews of Revolut and 2,882 reviews of BBVA Bancomer México were collected using structured scraping with the Google-Play-Scraper Python library from the Google Play Store. These spontaneous opinions complement with an emotional and experiential dimension. Both sources of information were treated confidentially and anonymously.

3.4 Quantitative Analysis: Survey and Sentiment Analysis

3.4.1 Survey Data Analysis

This study uses an adapted version of the UTAUT (Unified Theory of Acceptance and Use of Technology) model to analyse how factors such as trust, risk perception, and preference for traditional banking vary according to sociodemographic characteristics,such as country of residence. Since the primary objective is not to predict usage intention, but rather to comparatively explore how certain perceptions differ among groups, the use of independent sample tests was appropriate. These tests allow us to identify whether there are statistically significant differences in key variables (derived from Likert-type scales) between two groups - for example between users in Mexico and Ireland.

The questionnaire data were analysed exclusively using SPSS. were grouped into three constructs based on the UTAUT model Venkatesh et al. (2012), classifying them as: Digital Trust, Perceived Risk, and Traditional Banking Preference. A Pearson Correlation Matrix was subsequently developed between these constructs, identifying significant associations among trust, perceived risk, and preferences for traditional channels. A Student t-test (independent t-test) was also performed to compare significant differences between the Mexican and Irish Groups.

3.4.2 Sentiment Analysis of Reviews

A sentiment analysis was performed in Python (Google Colab) using scraping to obtain the reviews, following the sentiment analysis using libraries such as pandas, NumPy, seaborn, and matplotlib for data manipulation, analysis, and visualization, as well as multiple supervised models, including:

- Long Short-Term Memory (LSTM)
- Logistic Regression (LR)
- Random Forest (RF)
- Support Vector Machine (SVM)

Models were selected on because of having competitive advantages with regard to the handling of textual data. Logistic Regression, acting as a well-recognized baseline, gives interpretation to the classification processes. Random Forest stands for robustness against overfitting and efficiently manages feature variability. Support Vector Machines perform well in high-dimensional and unstructured datasets also less sensitive to overfitting and easier to interpret. Long Short-Term Memory (LSTM), belonging to recurrent neural networks, demonstrate their effectiveness in detecting complex sentiment patterns by capturing long-term dependencies in sequential data such as text Atmaja et al. (2023). These models have shown successful results in financial text analysis and prior sentiment predictions, as documented by Cicekyurt and Bakal (2025) and Bhowmik et al. (2025). To evaluate model performance, a combination of standard metrics, including accuracy, precision, recall, and F1 score, was used to obtain an objective assessment of sentiment classification. This emotional dimension complements our findings, as it identifies spontaneous patterns of trust, satisfaction or rejection of digital banking.

4 Design Specification

The analysis was based in two main components:

- Sentiment analysis of spontaneous reviews on banking apps from Revolut (20,000) and BBVA Bancomer México (2,882), collected via scraping.
- Statistical study of user perceptions using a structured questionnaire based on the UTAUT model applied in Mexico and Ireland.

4.1 General Architecture

4.1.1 Technical Pipeline:

As part of the solution design, a modular technical pipeline was defined to address the challenges of linguistic variability, emotional classification, and the scarcity of reliable labels. A dual approach (traditional machine models + deep learning model) was chosen to evaluate different supervised learning methodologies. Preprocessing included machine translation for compatibility with NLP tools, and class balancing was used to ensure equitable representation during training. Sequential tokenization and embedding made it possible to leverage more complex text structures, while performance metrics were designed to assess the robustness of each model under real-world scenarios.

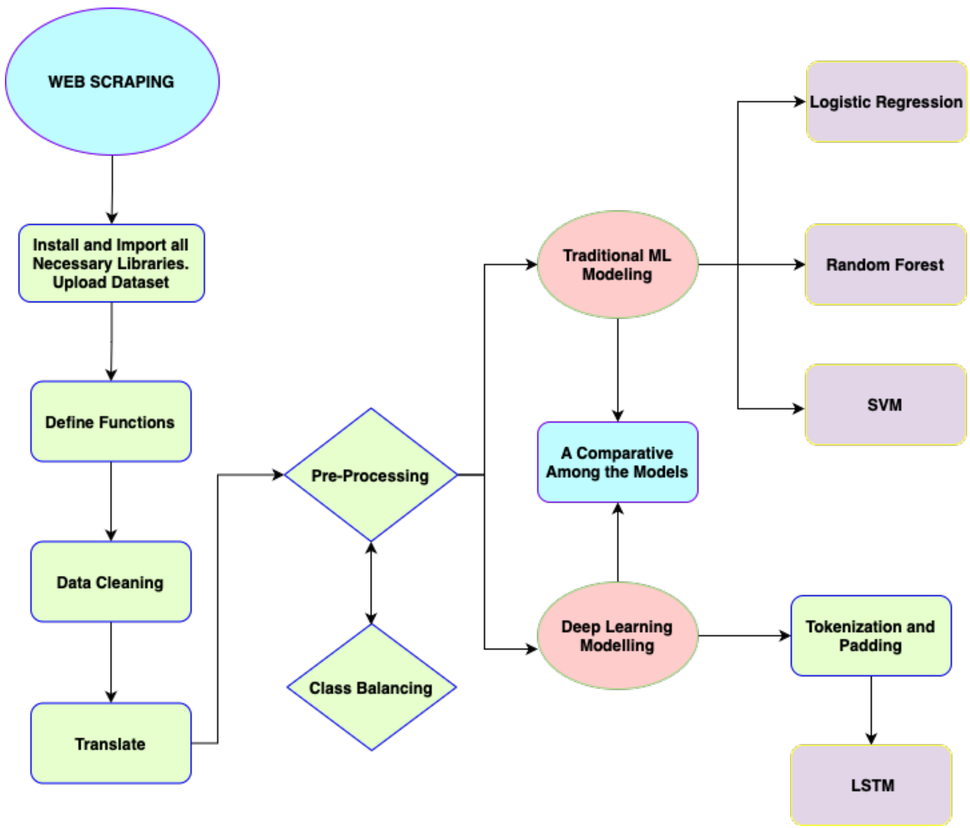


Figure 2: Pipeline Model

4.1.2 UTAUT Theoretical Model:

The UTAUT model was incorporated to understand the factors influencing the technological acceptance of the banking apps analysed. The key dimensions were performance expectancy, effort expectancy, social influence, and facilitating conditions. These variables allowed for structuring the collection and analysis of spontaneous reviews, linking individual perceptions with emotional patterns. The use of sentiment analysis complements the UTAUT approach by offering an automated reading of the affective content underlying user opinions, helping to indirectly assess usage intent, digital trust, and perceived barriers in the mobile financial environment.

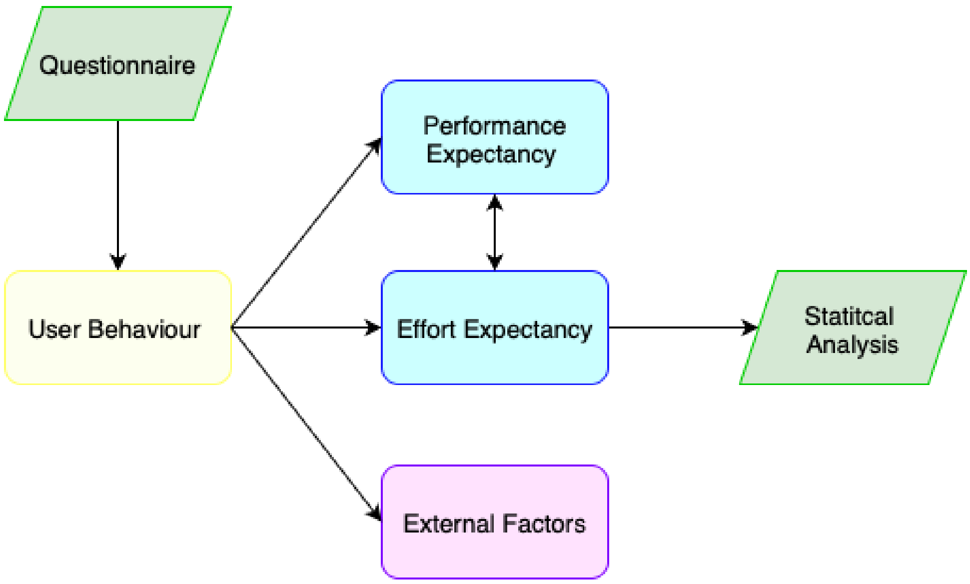


Figure 3: Research UTAUT Model-Adapted

5 Implementation

The entire process was implemented in Google Colab, starting with the extraction of reviews from the Google Play Store using the Google-Play-Scraper Library. Next, it was decided to use Machine Learning models (LG, RF, SVM) as well as Deep Learning (LSTM). In a separate notebook, the necessary libraries were applied and imported to begin the analysis.

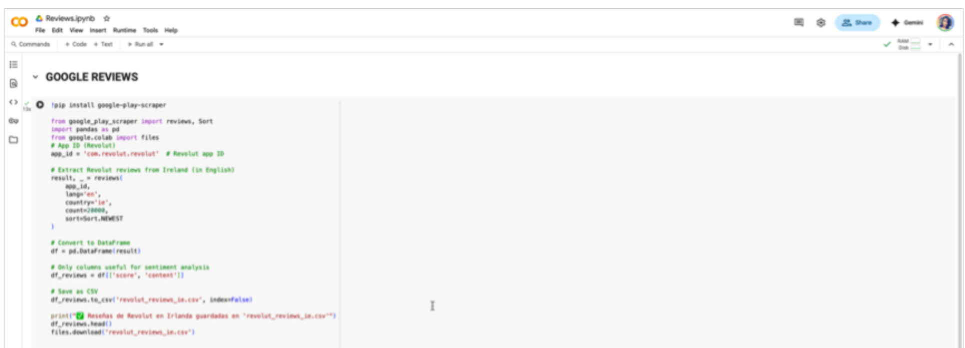


Figure 4: Web scraping

Then, the BBVA and Revolut reviews datasets were loaded in .CSV format (it is worth mentioning that separate notebooks were created for each dataset). Then, functions were defined to assist in text cleaning, language detection, automatic translation (when needed), lemmatization, and textual noise removal. These steps were applied to both the ML and DL pipeline. To reduce class imbalance in the data, subsampling balancing was applied to the training sets, use for both ML and DL models, this technique ensured equitable representation across sentiment categories (positive, negative, and neutral), improving the model's robustness to unbalanced classes.

```python
# Check class distribution before balancing
print("Sentiment distribution before balancing:")
print(df["sentiment"].value_counts())  # FIXED: was "content", should be "sentiment"
print(f"Total samples: {len(df)}")

# Show percentage distribution
print("\nPercentage distribution:")
print(df["sentiment"].value_counts(normalize=True) * 100)

# Separate data by sentiment
positive_reviews = df[df["sentiment"] == "Positive"]  # FIXED: was "content"
negative_reviews = df[df["sentiment"] == "Negative"]  # FIXED: was "content"
neutral_reviews = df[df["sentiment"] == "Neutral"]    # FIXED: was "content"

print(f"\nClass sizes before balancing:")
print(f"Positive: {len(positive_reviews)}")
print(f"Negative: {len(negative_reviews)}")
print(f"Neutral: {len(neutral_reviews)}")

# Set target sample size (based on minority class)
min_samples = min(len(positive_reviews), len(negative_reviews), len(neutral_reviews))
print(f"\nTarget sample size per class: {min_samples}")

# Check if balancing is actually needed
max_samples = max(len(positive_reviews), len(negative_reviews), len(neutral_reviews))
imbalance_ratio = max_samples / min_samples

print(f"Imbalance ratio: {imbalance_ratio:.2f}")

if imbalance_ratio < 2.0:
    print("Dataset is relatively balanced. Balancing may not be necessary.")
else:
    print("Dataset is imbalanced. Proceeding with balancing...")

# Undersample each class to the same size
balanced_df = pd.concat([
    positive_reviews.sample(min_samples, random_state=42),
    negative_reviews.sample(min_samples, random_state=42),
    neutral_reviews.sample(min_samples, random_state=42)
])

# Shuffle the balanced dataset
balanced_df = balanced_df.sample(frac=1, random_state=42).reset_index(drop=True)

# Show balanced class distribution
print(f"\nSentiment distribution after balancing:")
print(balanced_df["sentiment"].value_counts())  # FIXED: was "content"
print(f"Total balanced samples: {len(balanced_df)}")

# Verify all columns are preserved
print(f"\nColumns in balanced dataset: {balanced_df.columns.tolist()}")

# Show data reduction
original_size = len(df)
balanced_size = len(balanced_df)
reduction_percent = ((original_size - balanced_size) / original_size) * 100

print(f"\nData reduction: {original_size:,} -> {balanced_size:,} ({reduction_percent:.1f}% reduction)")

# Quick verification of balanced data
print(f"\nFirst 5 samples from balanced dataset:")
print(balanced_df[['sentiment', 'processed_text']].head())

# Update df to use balanced dataset for further processing
df_balanced = balanced_df.copy()
print(f"\nBalanced dataset ready for machine learning!")
```

Figure 5: Class Balancing

For the LSTM model, the texts were tokenized and padded to standardize the length of the input sequences. A bidirectional LSTM network was trained, optimized using techniques such as early stopping, dynamic learning rate reduction, and automatic checkpoints to avoid overfitting. Finally, the trained model was applied to the entire set of reviews in a massive sentiment prediction process. The results were evaluated using metrics such as accuracy, F1 score, precision, and recall.

In parallel, for Traditional ML Models (LR, RF and SVM), the pre-processed texts were vectorized using the TF-IDF (Term Frequency–Inverse Document Frequency) technique. These numerical representations fed into traditional classification models. Each model was trained and evaluated independently, and its results were compared against the LSTM model in terms of both accuracy and computational efficiency.

Likewise, a structured digital questionnaire (Google Forms) was designed in a version adapted to the UTAUT model, focusing solely on two fundamental constructs: performance expectancy and effort expectancy, in addition to an external factor: Perceived Risk.

The objective of this research was to measure perceptions about trust in digital banking, risk, and the use of traditional channels in digital banking services. The questionnaire initially contained 17 questions, written in English and Spanish.

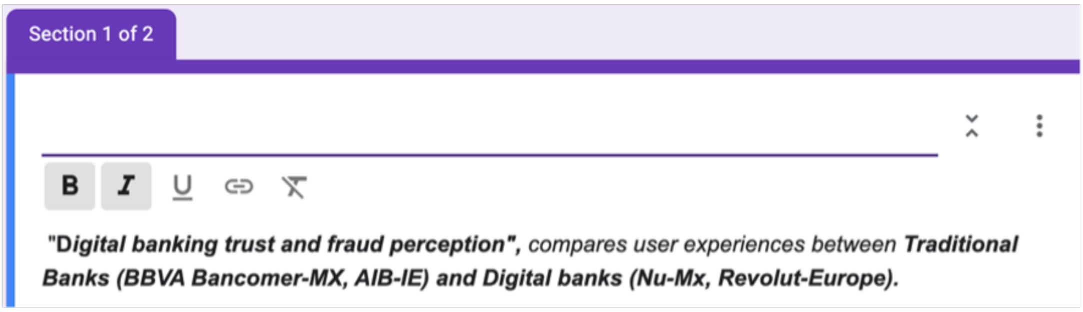


Figure 6: Questionnarie

From this set, were identified those that showed the greatest theoretical consistency with the model's constructs were selected, ultimately grouping them into three key dimensions: Total Trust in Digital Banking, Perceived Risk and Traditional Banking Preference. The questions used a 5-point Likert scale to measure participants' level of agreement.

The form was distributed digitally, generating a structured data set that was then processed and analysed in SPSS. To evaluate significant relationships between the constructs, a Pearson Correlation Matrix was calculated. Additionally, a Student T-Test was applied to statistically compare the results between participants in Mexico and Ireland, allowing for the identification of cultural differences in the perception of digital banking services.

6 Evaluation

6.1 Comparison of Classification Models

6.1.1 Revolut

The supervised models were trained and evaluated using data from Revolut. The comparison was based on standard evaluation metrics: accuracy, precision, recall, and F1 score, to ensure a balanced evaluation across classes

Model	Accuracy	Precision (macro avg)	Recall (macro avg)	F1-score (macro avg)	Training Time
LR	0.7695	0.78	0.77	0.77	1.0160 s
RF	0.7695	0.78	0.77	0.77	2.9522 s
SVM	0.7634	0.78	0.76	0.77	0.5801 s
LSTM	0.77	0.77	0.77	0.77	422.03 s (7.03 m)

Figure 7: Revolut Outcome

The performance of all tested models remained nearly identical with accuracy values between 76.34% and 76.95% and equivalent macro-average precision and F1-scores (0.77–0.78). Among the models LR and RF maintained equivalent accuracy scores of 76% yet LR emerged as the best choice since it trained in the least amount of time (1.01 s). The accuracy and overall metrics of RF matched LR yet the training time of RF was almost three times longer than LR (2.95 s).

LSTM model showed competitive results through its 77% accuracy score and balanced precision alongside recall and F1-scores. The model required substantially longer training duration (422.03 s / 7.03 min) because of its complex computational nature. The complex nature of LSTM enables it to learn deep contextual connections in text which makes it better suited for multilingual data and longer documents and larger datasets at the expense of increased computation requirements.

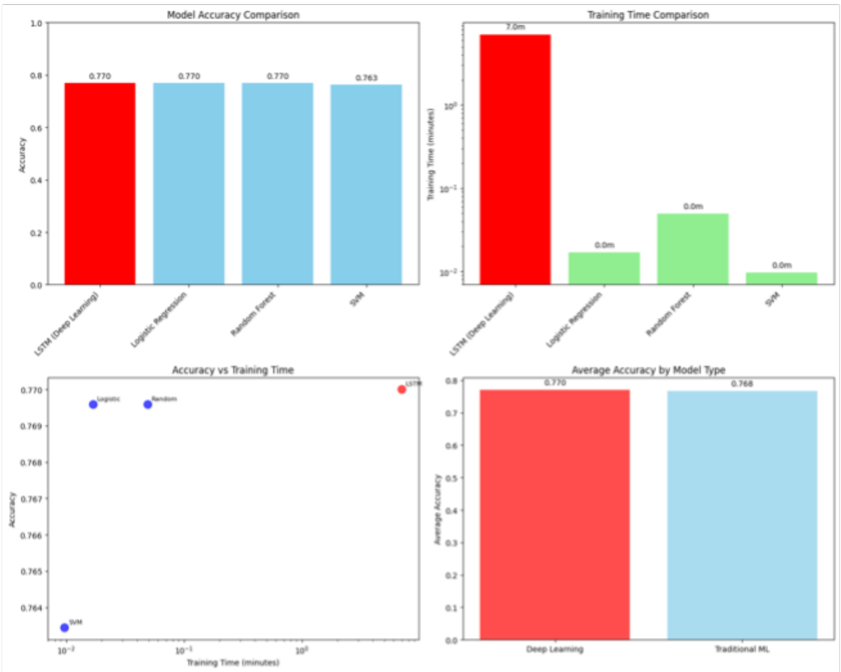


Figure 8: Comparative Performance of ML and DL Models (Revolut Dataset)

6.1.2 BBVA Mexico

The supervised models were trained and evaluated using data from BBVA. The comparison was performed using standard evaluation metrics: accuracy, precision, recall, and F1-score, to ensure a balanced evaluation across classes.

Model	Accuracy	Precision (macro avg)	Recall (macro avg)	F1-score (macro avg)	Training Time
LR	0.7230	0.73	0.72	0.73	0.0378 s
RF	0.7179	0.73	0.72	0.72	0.7194 s
SVM	0.7025	0.72	0.70	0.71	0.0734 s
LSTM	0.75	0.77	0.74	0.75	214.06 s (3.57m)

Figure 9: BBVA Outcome

In this case, the LSTM model outperformed traditional models in all key metrics except training time. With an accuracy of 75% and an F1 score of 0.75, LSTM was the best overall performer for classifying sentiment in BBVA reviews. Despite the higher computational cost, its ability to capture contextual sequences gave it an advantage over TF-IDF-based models.

Due to its efficiency and good balance, Logistic Regression remains a valid option in processing-constrained environments, although in this case it did not outperform the deep model.

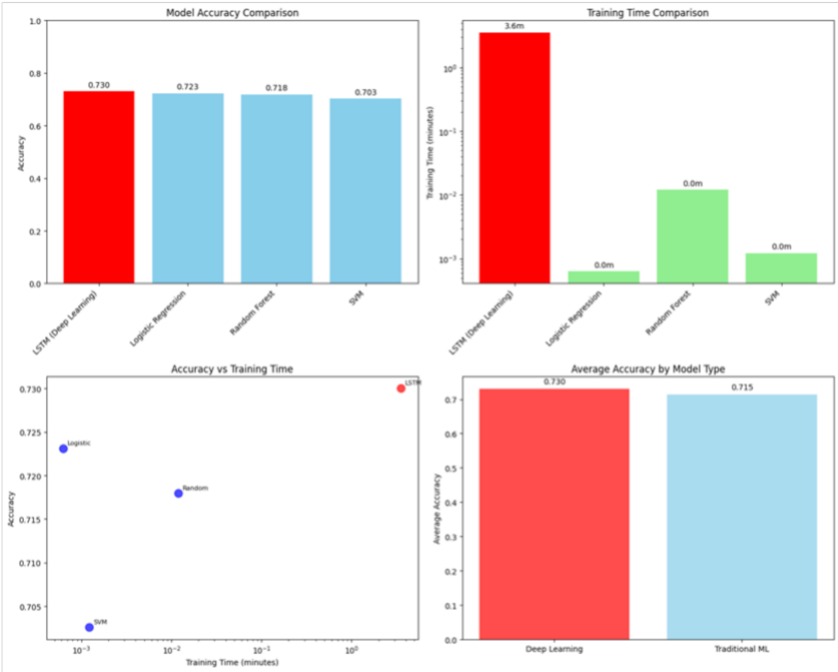


Figure 10: Comparative Performance of ML and DL Models (BBVA)

6.2 UTAUT MODEL

6.2.1 Pearson Correlation Matrix

		Preferance_traditional_Banking	Total_Trust	Risk_Perception
Preferance_traditional_Banking	Pearson Correlation	1	.341**	.293*
	Sig. (2-tailed)		.007	.022
	N	61	61	61
Total_Trust	Pearson Correlation	.341**	1	.376**
	Sig. (2-tailed)	.007		.003
	N	61	61	61
Risk_Perception	Pearson Correlation	.293*	.376**	1
	Sig. (2-tailed)	.022	.003	
	N	61	61	61

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 11: Pearson Correlation Matrix

The Pearson correlation matrix was used to analyze the UTAUT adapted model construct relationship from questionnaire data (N=61). The three studied constructs included: Total Trust (digital trust) and Traditional Banking Preference (traditional channel preference) and Perceived Risk (risk perception). The statistical analysis indicates meaningful correlations among all variable pairs:

- **Total Trust and Traditional Banking Preference** show a moderate positive correlation (r = .341, p = .007), indicating higher trust in digital banking can coexist with a preference for traditional channels, rather than replacing them entirely.
- **Total Trust and Perceived Risk** also show a positive correlation (r = .376, p = .003), indicating that, in some cases, greater perceptions of trust can coexist with risk awareness.
- **Traditional Banking Preference and Perceived Risk** show a weaker but significant correlation (r = .293, p = .022), indicating that those who perceive greater risk tend to prefer conventional banking channels.

6.2.2 T Test Independent Samples

1. Total Trust

Total Trust				
Country	Mean	Std. Deviation	t	Two-Sided p
Ireland (1)	3.27	.727	.011	.991
Mexico (2)	3.27	.750		

Figure 12: T Test Results for Total Trust by Country

T-test analyses indicated no statistically significant differences between countries in terms of trust banking. This suggests cross-national homogeneity in this variable, which may indicate that experiences and attitudes toward digital banking services are similar regardless of the geographic context assessed.

2. Perceived risk

Perceived Risk				
Country	Mean	Std. Deviation	t	Two-Sided p
Ireland (1)	3.02	.793	-.003	.997
Mexico (2)	3.02	.830		

Figure 13: T Test Results for Perceived Risk by Country

The t-test results that there is no statistically significant differences in perceived risk in the means, both groups reported similar perceptions of risk in digital transactions.

3. Traditional banking preference

Traditional Banking Preference				
Country	Mean	Std. Deviation	t	Two-Sided p
Ireland (1)	3.19	.934	-1.386	.171
Mexico (2)	3.51	.852		

Figure 14: T Test Results for Traditional Banking Preference by Country

The t-test results indicate that the mean score for Mexico (3.51) is slightly higher that Ireland (3.19), this suggested that Mexicans may still prefer traditional channels, however, this difference is not statistical significant (p=.171), indicates that both countries show similar preferances for traditional banking.

6.3 Discussion of Results

The study's findings provide a deep understanding of the perception of digital banking services from a multicultural perspective, combining machine learning with theoretical models of user behavior. During the analysis of both Revolut and BBVA datasets, traditional machine learning (ML) models such as Logistic Regression and Random Forest yielded similar results 76.95% for Revolut and 71-72% for Bbva in accuracy. These results were compared with LSTM model 77% for revolut and 75% for Bbva in accuracy, reflecting minimal difference in accuracy. However, traditional models demonstrated a clear advantage in training time efficiency, whereas the LSTM requires high computational resources without showing a significant improvement in predictive performance.

On the other hand, the correlation analysis showed that Total Trust in Digital Banking, Traditional Banking Preference, and Perceived Risk had significant associations with each other. These correlations support the hypothesis that institutional trust and risk perception affect user preferences for traditional channels, reaffirming what has been observed in previous studies on technology acceptance in financial services [9]. Furthermore, independent samples t-tests showed no statistically significant differences between the Mexican and Irish groups in any of the constructs. The results indicate a possible cultural alignment in users' perceptions of digital banking..

Revolut receives recognition as a European fintech innovation leader, yet BBVA Bancomer has implemented significant changes in its digital offering, including advanced security tools, artificial intelligence applied to customer service, and optimized mobile experiences. However, sentiment analysis results and questionnaire responses suggest that these efforts do not always translate into a proportional perception of trust among Mexican users, possibly due to broader cultural or institutional factors BBVA México (2025)

6.4 Design Criticism:

The quantitative approach combining structured survey data and sentiment was appropriate for capture the evidence; however, the limited sample size in the questionnaire (n=61) diminished the statistical power of the analyses. Furthermore, voluntary selection through social media likely generated bias that affected the diversity of the participants.

Regarding sentiment analysis, the original datasets exhibited significant class imbalance, to mitigate this, a class-balancing under sampling was applied, however the limited size of user reviews constrained model generalizability and may have affected the reliability of sentiment classification outcomes."

6.5 Suggestions for Improvement:

For future studies, it is recommended to increase the questionnaire sample size and use a stratified sampling technique based on age, gender, and educational level. Likewise, it would be valuable to explore other deep learning models (such as RNNs) that improve the labelling process, resulting in improved training and interpretation quality.

7 Conclusion and Future Work

This study analysed the perception of trust and risk in digital banking services using quantitative approach, combining ML and DL techniques with a survey adapted from the UTAUT model. The integration of automated sentiment analysis of spontaneous user reviews with structured questionnaire data enabled a comprehensive quantitative assessment capturing both emotional and rational aspects of financial behaviour.

DL models such as LSTM demonstrated similar performance to traditional ML methods (LR, RF), although they required more processing power. Statistical analyses showed that user perception was significantly linked to trust, perceived risk, and preference for traditional channels, However, independent samples t-tests showed no statistically significant differences between Mexican and Irish participants in any of these constructs

The research evidence demonstrated that institutional trust, along with risk perception, remain essential elements for the technological adoption of digital banking platforms. Furthermore, the automated emotional analysis system provides researchers with an additional tool for studying consumer behaviour, allowing for better interpretation of large-scale sentiment patterns. The research findings pave clear paths for future studies to build upon this work. Researchers need to expand their questionnaire sample to obtain more representative findings, which would also benefit from considering diverse socio-technological regions.

From a technical perspective, it is suggested to explore more advanced deep learning architectures such as RNNs, which produce better results in text classification and contextual analysis tasks. It would also be valuable to integrate more detailed sentiment analysis, including irony detection or emotional ambiguity, to improve automatic content interpretation.

Furthermore, future research should expand the application of the UTAUT model, incorporating additional dimensions such as facilitating conditions or behavioural intention, in addition to conducting longitudinal analyses to monitor changes in risk perception and trust over time.

Future research should examine the emotional impact on current user behaviour by combining digital tracking data with data mining methods to confirm how emotions affect daily financial decisions.

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