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Factors Influencing the Adoption of Natural Language Processing of Commercial Banks in Vietnam

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Abstract

In the digital age, the adoption of natural language processing (NLP) has emerged as an inevitable trend in the banking sector, supporting the reduction of time and costs, optimizing data management, and enhancing customer experience. However, the adoption of NLP in commercial banking activities in Vietnam faces significant challenges. The study utilized a multivariate regression model and SPSS software to examine the influence of six factors: Compatibility, Technical Complexity, Business Orientation, Human Resources, Legal Corridor, and Market Uncertainty. The results showed that three factors, namely Technical Complexity, Business Orientation, and Legal Corridor, affect the adoption of NLP in commercial banks in Vietnam. Based on these findings, the research team proposed several recommendations and solutions to accelerate the adoption of NLP in Vietnam.

Keywords: Artificial intelligence (AI), Digital transformation, Natural language processing (NLP).

1. Introduction

The fourth industrial revolution is currently unfolding on a global scale, marked by the advent of transformative technologies such as artificial intelligence (AI). These technologies are playing pivotal roles across various sectors, with the finance and banking industry being particularly affected. Banks in Vietnam, as well as globally, have begun to integrate Natural Language Processing (NLP) into several management-related functions. This integration aids banks in achieving operational stability and identifying solutions to enhance profitability. However, the full potential of NLP remains underutilized due to several constraints that impact its adoption within the banking sector.

In response to this, our research team proposes a model to examine the factors affecting the adoption of Natural Language Processing (NLP) in commercial banks in Vietnam. Analyzing this model is crucial, as the research findings will provide valuable insights and recommendations for bank managers and policymakers, aimed at improving the implementation and effectiveness of NLP in commercial banks throughout Vietnam.

2. Literature Review

Fridgen et al. (2022) evaluated the applicability of AI in the retail banking sector in Germany. Through the participation of 23 IT experts with deep knowledge of AI, this study applied the Technology-Organization-Environment (TOE) framework to analyze factors influencing the integration of AI into banking systems. The results indicated that not only do the factors within the TOE model affect individual processes, but they also influence in various ways throughout the digital technology adoption process in banking. From this, the research team identified 12 factors that most significantly affect the adoption of AI in this sector, including: (1) The bank's relative advantage, (2) The availability of facilities and technology, (3) The safety and security of the technology used, (4) The efficiency of the bank's investment in technology, (5) The consensus of senior management, (6) Resource factors within the bank, (7) The expertise of the human resources, (8) The ability to restructure the management apparatus, (9) The size of the bank, (10) Competitive pressure from other organizations, (11) Legal factors when applying technology in banking, and (12) The trend of using AI across the industry.

Van Phuoc (2022) research focused on the factors influencing the adoption of artificial intelligence in Vietnam. Using the structural equation method and based on 193 responses from businesses across Vietnam, this study indicated that management capacity is the most significant factor affecting the use of AI technology in businesses.

Conversely, organizational size and competitive pressure do not play a significant role in the process of AI adoption in businesses. Specifically, the study concluded the following important points: (1) Technical compatibility, (2) Relative advantage, (3) Management support, (4) Management capacity, (5) Organizational readiness, (6) Government involvement, (7) Market uncertainty, (8) Supplier partnership, all positively impact the intention to integrate AI technology in organizations in Vietnam. Organizational size and competitive pressure do not significantly affect the intention to adopt AI technology in organizations in Vietnam.

The research team of Horani et al. (2023) experimented with data from 512 senior IT/IS managers in public and private organizations in Jordan. The results indicated that several factors such as (1) Relative advantage, (2) Senior management support, (3) Cost efficiency, and (4) Compatibility positively influence the intention to adopt AI-based technologies. Additionally, factors such as (5) Legal frameworks and (6) Technical complexity of the technology were found to negatively affect the intention to adopt. These results complement previous studies and clarify the importance of technical compatibility in integrating AI into an organization's technological infrastructure.

3. Literature Review

3.1. Literature Review of Natural Language Processing

3.1.1. Natural Language Processing (NLP)

Natural Language Processing (NLP) is a subfield of computer science within the broader domain of artificial intelligence (AI) that aims to endow computers with the ability to comprehend text and speech similarly to humans (Machiraju & Moxdi, 2017). NLP models function by identifying relationships between linguistic elements, such as letters, words, and sentences within text datasets. This is a complex process requiring stringent technical specifications, encompassing multiple stages and diverse methodologies. Data preprocessing, feature extraction, and modeling are among the steps involved (DeepLearning.AI, 2023). Over time, NLP has undergone significant advancements driven by improvements in hardware, computer software, and linguistic theories (Qiu et al., 2020). The integration of computational linguistics with methodologies such as statistics, machine learning, deep learning, and deep neural networks has enabled NLP to decode and reconstruct natural language structures to achieve specific objectives. These objectives include information extraction, transforming unstructured text into structured formats, syntactic processing, semantic understanding, and identifying relationships between concepts. The research conducted by Klein et al. (2020), Lindvall et al. (2018), Robert and Cornwell (2013), and Velupillai et al. (2018) has elucidated these advancements. NLP is not only beneficial across various scientific disciplines but also applicable for multiple purposes such as language analysis, information retrieval, text translation, constructing conversational bots, text classification, sentiment analysis, and numerous other applications as indicated by Guamán et al. (2017) and Lázaro et al. (2024).

3.1.2. Adoption of Natural Language Processing in Banking

Firstly, in its capacity as a tool for reading, searching, and retrieving information, NLP aids in resume evaluation by integrating with the K-nearest neighbors (KNN) algorithm. This integration facilitates the filtering of resumes, extraction of key keywords, and classification of candidates based on their profiles to match them with appropriate positions (Elets BFSI, 2023). NLP also plays a crucial role in supporting the compliance processes of banks globally. Labeling unstructured data simplifies the search for digital document sets, enabling compliance agencies to assess adherence to standards and regulations (Reshma, 2018). NLP techniques can also be applied to scan documents, identify key regulatory entities, extract metadata, and interpret the main regulatory objectives outlined in the texts. By automating a substantial portion of the process, NLP not only mitigates the risk of human error but also reduces the likelihood of regulatory violations stemming from human perception and emotion. This allows financial institutions to comply with increasingly stringent regulations efficiently and optimize workflow (International Banker, 2021). Moreover, NLP is utilized as a search tool to advance financial markets. Financial institutions store vast volumes of documents in their databases. A search tool powered by NLP facilitates the retrieval of elements and concepts within these documents to gather valuable investment information. The system then displays a summary of the most pertinent information for search queries from financial company employees on the search tool interface (Reshma, 2018).

Expanding on its role as a "reader" capable of searching and retrieving documents, NLP also functions as a statistician, including quantifying large volumes of text and analyzing them to identify emerging signals. For instance, current voice analysis tools can "listen" to analysts' conference calls to detect the tone and sentiment behind what company leaders present, thus summarizing information and providing insights for equity analysis (Pereira & Shroff, 2022). NLP is also an effective technology in supporting the identification, creation, and analysis of eXtensible Business Reporting Language (XBRL) and other classification standards (e.g., Environment-Social-Governance standards) to enhance standardization in information disclosure, tailored to the specific characteristics of various industries. NLP can combine the analysis of structured data from numerical reports with unstructured data in financial reports by leveraging XBRL classification and running automated tests to verify internal consistency, compliance with minimum requirements, and alignment with economic trends and stakeholder expectations. Standardization, comparability, and interoperability can be achieved through NLP analysis, aiding drafters in understanding stakeholder expectations (Faccia et al., 2021). Utilizing NLP tools for text analysis, unstructured data sources frequently used by investors can be converted into a single enhanced format, specifically optimized for financial applications. This intelligent format facilitates the generation of impactful data analyses by making structured data readable and visualizable, thereby enhancing the efficiency and accuracy of data-driven decisions. The text analysis functionality of NLP is applied in various financial operations with distinct characteristics (Reshma, 2018). Sentiment analysis is one of the most common objectives of text analysis and is also a crucial factor in forecasting stock and financial markets (Poria et al., 2016). By combining sentiment analysis capabilities and leveraging NLP's intelligent documents, financial companies can identify the most sought-after services, key customer challenges, and their perceptions of the company, and monitor market reactions to significant events. The results obtained can be used to create personalized incentives, evaluate customer feedback, and improve product and service quality (Staff GBAF Publications Ltd., 2023).

Text analysis is also primarily utilized for fraud detection, risk management, investment evaluation, and alpha generation in the financial domain. NLP can analyze large volumes of transaction data and account activity to identify transaction patterns based on the type of transaction, amount thresholds, channels, etc., of potentially fraudulent activities. In this way, NLP generates alerts and triggers preventive measures to mitigate losses for customers and organizations. Furthermore, NLP is applied in the financial sector to analyze loan applications, evaluate financial and credit reports, measure customer reliability, and automate loan underwriting processes. Additionally, NLP can scrutinize business plans to assess the borrower's consistency and attitude based on the wording and expressions in the documents. Integrating NLP in financial institutions helps optimize evaluation processes, minimize manual work, and enhance decision accuracy. NLP techniques also play a significant role in analyzing company profiles, earnings reports, and articles to assess investment opportunities and construct risk models. For portfolio managers, NLP aids in making intelligent decisions and managing risk effectively (Elets BFSI, 2023). NLP also achieves the goal of content enrichment in the financial sector by identifying and distinguishing the most engaging thought leadership blogs compared to competitors, while providing a personalized customer experience through content tailored to potential customers (Reshma, 2018).

Lastly, with customer support and chatbot functionalities, NLP can analyze and predict to handle voice and text commands, quickly responding to queries and assisting in various financial transactions, effectively meeting customer needs (Staff GBAF Publications Ltd., 2023; Elets BFSI, 2023). Chatbots are not only tools for providing 24/7 customer support on simple issues such as money transfers, setting up recurring payments, checking bank statements, and detecting customer spending habits but also have the capability to use multi-context scenarios and conduct natural dialogues (Neto & Fernández, 2019). This application allows customers to access information and explore additional services without visiting bank branches; instead, they can interact through an online messaging system from laptops or smartphones. The implementation of chatbots brings numerous benefits to the banking industry, including enhancing customer experience, reducing response time, and increasing customer satisfaction, as has been implemented by most major banks (Barnes, 2024; Elets BFSI, 2023).

In the banking sector, the application of NLP is becoming increasingly prevalent, not only for extracting structured information from unstructured content but also for synthesizing natural language. Financial applications of NLP must meet specific requirements such as using time-split data to prevent "leakage" of future information into the past, along with achieving high accuracy and low latency. In contrast, other fields like healthcare and education may have different requirements. Although the focus has been on fully automated NLP applications in finance, it is important to consider human-performed NLP applications, such as computer-assisted interactive trading (İrsoy et al., 2019) or computer-assisted drafting of research reports (Chen et al., 2020). This highlights that the combination of human and technology is essential to achieving optimal results in these fields. Therefore, continued discussion and research in the field of NLP in finance are crucial to ensure sustainable progress and meet the practical needs of the industry (Capponi & Lehalle, 2023).

3.1.3. Status of Natural Language Processing Adoption in Vietnamese Commercial Banks

Commercial banks in Vietnam are in the nascent stages of utilizing NLP, a component of AI, with significant developmental potential. In practice, in Vietnam, 41% of financial institutions have adopted NLP to personalize their marketing strategies for their customer segments. This trend is expected to continue, with 45% of respondents in a survey by Finastra in Vietnam focusing on improving customer service through AI (Barnes, 2024). As of January 2024, 15 out of 43 commercial banks have implemented chatbots. Among these, the majority have deployed chatbots on the Facebook platform (14/17), with some also integrating chatbots on websites (5/17) and mobile applications (7/17) (Vũ et al., 2024). Some banks invest in self-developing technology, while others opt for outsourcing technology development. Many banks choose outsourcing to rapidly access technology and provide customers with professional experience, despite the inherent advantages and disadvantages of each approach (Hương & Bình, 2022).

Notably, the adoption rate of AI chatbots by 34.9% of commercial banks in Vietnam, compared to only 8% in the United States according to Shevlin (2021), signifies the robust commitment and determination in applying advanced technology. It can be affirmed that Vietnamese banks have made substantial investments in technology systems to adapt to changing consumer trends, demands for financial services, and the rapid evolution of new technological waves. Modern technology not only enhances operational efficiency and reduces costs for banks but also ensures safer and more transparent transactions (Thu, 2021).

3.2. Theoretical Background

The study of factors influencing the application of natural language processing (NLP) technology is based on the following theoretical frameworks:

3.2.1. Theory of Reasoned Action - TRA

The Theory of Reasoned Action (TRA) is a model in social psychology and human behavior aimed at explaining and predicting human behavior based on their motivations and thoughts. TRA posits that human behavior is contingent upon the close link between attitude and outcome. It asserts that an individual's behavior in performing a specific action directly arises from their behavioral intention (Fishbein & Ajzen, 1975).

3.2.2. Theory of Planned Behavior - TPB

Building on the principles of TRA, Ajzen (1991) extended the model by incorporating the independent variable "perceived behavioral control," which considers the perceived ease or difficulty in performing the desired behavior. Behavioral intention is a crucial predictor of human behavior. According to the TPB, behavioral intention is formed by three main factors: attitude toward the behavior, subjective norms, and perceived behavioral control. Attitude toward the behavior refers to the degree to which a person values or disvalues a behavior. Subjective norms refer to a person's perception of what others think they should do. Perceived behavioral control refers to the extent to which a person believes they can perform a particular behavior. The more positive the attitude towards the behavior, the more supportive the subjective norms, and the fewer the perceived barriers, the stronger the behavioral intention (Ajzen, 1991).

3.2.3. Technology Acceptance Model - TAM

The Technology Acceptance Model (TAM), introduced by Davis et al. (1989) and based on the TRA, is used to explain and predict behavior related to technology acceptance and usage. The core of this model focuses on describing the impact of technical factors on individual decisions regarding the acceptance and intended use of technology. TAM aims to explain the general determinants of computer acceptance, leading to an understanding of user behavior with computer technologies on a broad scale. The model indicates that when users interact with new technology, key factors influencing their decision to use it include perceived usefulness (PU) and perceived ease of use (PEU). TAM is often employed in studies involving human-computer interaction and information technology in general, asserting that PU and PEU are crucial antecedents of the behavioral intention to use IT (Davis et al., 1989).

3.2.4. Unified Theory of Acceptance and Use of Technology - UTAUT

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a significant theory in the field of technology usage behavior research, developed by Venkatesh et al. (2003). It is based on various models and theories, including the Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM, TAM2), Motivational Model (MM), combined TAM and TPB, Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT).

UTAUT provides a useful tool for managers and researchers to evaluate the potential success of new technology adoption within an organization or community. Due to its utility, the model has been widely applied in various fields, including information systems, e-commerce, healthcare, and education. Introducing new technology can often be challenging due to user resistance, especially among those reluctant to change. To address this issue, based on UTAUT, managers can design specific interventions, such as training programs or marketing campaigns, to create a more favorable environment for users, helping them to accept and effectively use new technology. This is particularly important in promoting transformational development within organizations and society (Venkatesh et al., 2003).

4. Research Methodology

4.1. Sample Selection

This study employs a quantitative approach to evaluate the impact of factors identified through qualitative research on the use of Natural Language Processing (NLP) by commercial banks in Vietnam. The research utilizes descriptive statistics, factor analysis, correlation analysis, and multivariate regression analysis

Initially, the authors will employ descriptive statistical analysis to collect, synthesize, and analyze primary and secondary data to achieve the study's objectives. This tool is used to provide a comprehensive description of the relationships between factors influencing the use of Natural Language Processing (NLP) in commercial banks in Vietnam. Subsequently, factor analysis assists the authors in assessing the reliability of the measurement scale and testing the exploratory components. Cronbach's Alpha reliability coefficient is used to evaluate the quality of the scale and determine the appropriateness of the observed variables and scale in the research model using collected survey data. Exploratory Factor Analysis (EFA) will be utilized to assess the convergence of the observed variables and identify the impacting factors. Correlation analysis helps in examining the relationships between influencing factors and the affected factor. Thereafter, the authors use multivariate regression analysis to examine the interactions between the affected factor and influencing factors (Binh, 2023).

Furthermore, the mediating variable must satisfy three conditions: the independent variable explains the variance of the mediating variable, the mediating variable explains the variance of the dependent variable, and the presence of the mediating variable reduces the relationship between the independent and dependent variables (Binh, 2023).

4.2. Research Model and Hypothesis Proposals

4.2.1. Research Frame

The research team chose this topic in the hope of creating a useful reference document, providing suggestions for bank administrators and lawmakers to improve the quality of NLP implementation in commercial banks in Vietnam. The team consulted concepts, theories, and results from similar researchs. From the collected data, the team creates a hypothesis and research model, including independent variables and dependent variables. These hypotheses and models are built on basic theories and previous research in similar fields. Then, the team conducted a quantitative survey to choose the appropriate scale for the variables in the official research model. Based on that, the team conducted preliminary quantitative research and formal quantitative research. Finally, the SPSS is used to process and analyze survey data and evaluate research results. Therefore, give conclusions and propose solutions, while also pointing out limitations and suggesting analytical directions for future research.

4.2.2. Research Hypotheses

Based on foundational theories: Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), Unified Theory and Acceptance of Technology Use (UTAUT) along with the actual situation in the Vietnamese market, the research team selected 06 factors affecting the adoption of Natural Language Processing (NLP) in commercial banks in Vietnam.

4.2.2.1. Compatibility Factor (TT)

Nowadays, with the trend of applying artificial intelligence being considered the destination of most businesses globally, commercial banks in Vietnam are still racing with technology to keep up with the development of the industry. world. Having the ability to adapt and expedience will be a lever to help banks be more competitive compared to other banks (Deepalakshmi, 2019). In particular, the compatibility of artificial intelligence technology with available digital platforms will determine the risk of investing in new technology development. After considering the above factors, the research team hypothesized as follows:

Hypothesis H1: Technology compatibility positively affects the adoption of NLP in commercial banks in Vietnam.

4.2.2.2. Trust Factor (TC)

Nowadays an ever-changing environment, with massive volumes of data, has accelerated the processing speed and precision of modern innovations. Experts must continually update algorithms, structures, and technological networks to match this development requirement. However, this has increased the technical complexity of those technologies, particularly in AI and Natural Language Processing (NLP), both of which rely heavily on data. Data and information are used as sources to generate important insights. In Vietnam, the adoption of artificial intelligence to specific activities and operations in organizations is still relatively new, resulting in issues such as lack of maturity, technological ability, and specialists, as well as long development durations and expensive prices. As a result, firms tend to delay internal adoption of a complex technology until they have accumulated sufficient technical knowledge to successfully deploy and operate it (Attewell, 1992). Therefore, the research team hypothesized as follows:

Hypothesis H2: Technical complexity negatively affects the adoption of natural language processing (NLP) in commercial banks in Vietnam.

4.2.2.3. Bank Orientation Factor (DH)

Business orientation is always considered as a guideline for the human resources team to be able to operate the business seamlessly and organized. Therefore, the top apparatus' decision plays a significant role in the company's development orientation. As members with senior roles in the apparatus, they are always affected by factors such as risk, development potential and competitiveness with other financial entities. However, the banks considered to have a smart strategic orientation are those that know how to develop in the direction of innovation, initiative, and good risk management. These are also factors that weigh heavily on the decision to apply NLP in the banking organization. From there, the team posed the following hypothesis:

Hypothesis H7: The bank's orientation affects the adoption of NLP in commercial banks in Vietnam.

4.2.2.4. Human Resources Factor (NL)

Human resources play a critical role in the implementation of Natural Language Processing (NLP) in banks. In the current era of digital transformation, technology and artificial intelligence are widely used by most banks to optimize management and operations. Therefore, banks need to have a highly skilled and well-qualified workforce to utilize Natural Language Processing (NLP) proficiently. Based on this, the research team proposes the following hypothesis:

Hypothesis H4: Human resources positively influenced the adoption of Natural Language Processing (NLP) in commercial banks in Vietnam.

4.2.2.5. Legal Corridor Factor (PL)

Currently, in Vietnam, there are no legal documents specifically applied to the use of Natural Language Processing (NLP) in the commercial banking sector. With the current regulations, banks have been proactive in innovating and applying technical solutions that are compatible with the legal *corridor* while ensuring safety, controlling risks, and facilitating customers in the context of digitalizing services and instantaneous online transactions with a global reach. However, when the legal framework still has limitations, banks have faced difficulties in recording accounting transactions and in providing services to customers. Based on these observations, the research team proposes the following hypothesis:

Hypothesis H5: The legal corridor positively influences the adoption of Natural Language Processing (NLP) in commercial banks in Vietnam.

4.2.2.6. Market Uncertainty Factor (KCC)

Recently, the socio-economic landscape has been marked by market uncertainty, influenced by various factors such as the COVID-19 pandemic, geopolitical tensions, trade wars, and energy crises. This volatility poses challenges for businesses in terms of data collection, risk management, and accurate predictions. As a result, the utilization of AI in general, and NLP in particular, with adaptable and correct approaches to address these issues, becomes crucial. Banks and other financial institutions also believe that embracing new technology at a faster pace than their competitors will ensure they maintain a competitive edge and play a pivotal role in operational efficiency. Furthermore, it has been observed that the COVID-19 pandemic, a factor contributing to market uncertainty, has paved the way for the swift penetration of AI in businesses, highlighting its proficiency like never before. Hence, the research team proposes the following hypothesis:

Hypothesis H6: Market uncertainty positively affects the adoption of NLP in commercial banks in Vietnam.

4.2.3. Proposing Framework

Research model is presented by the diagram.

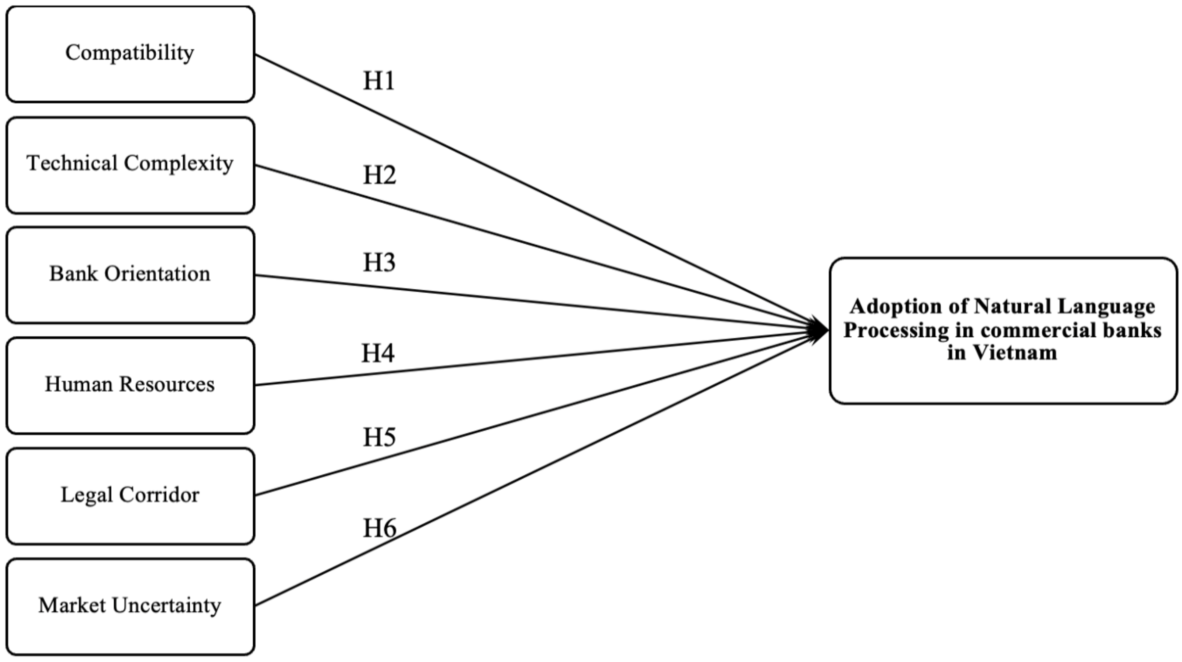

Figure 1. Research framework on factors affecting the adoption of Natural Language Processing in commercial banks in Vietnam.

4.3. Measurement Method

This article utilizes a quantitative research method, based on synthesizing previous studies, constructing a research model, and testing it through conducting surveys and collecting opinions from experts and professionals in the commercial banking sector in Vietnam. The concepts in the research model are measured using a 5-point Likert scale, with a total of 25 observed variables and 06 factor components. This scale measures the degree of agreement of the participants from "Strongly Disagree" to "Strongly Agree" concerning the related observed variables.

The dependent variable Likert scale "Adoption of Natural Language Processing in commercial banks in Vietnam" - denoted as UDCN, is measured by 6 criteria:

UDCN 1 - My bank is technologically compatible with the solutions provided by NLP.

UDCN 2 - I have mastered the operation and use of applications developed by NLP.

UDCN 3 - My bank is strategically ready for the adoption process of NLP.

UDCN 4 - My colleagues and I possess sufficient knowledge and experience to handle potential issues when using NLP technology

UDCN 5 - There are adequate policy mechanisms for digital transformation - applying NLP in banking.

UDCN 6 - My bank prioritizes the development of NLP during times when the market fluctuating.

5. Research Results

5.1. Analyze and Discuss Research Results

Table 1. Descriptive statistics of variables in the model.

Descritive Statistics					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
TT	181	1	5	3.99	0.854
PT	181	1	5	2.25	1.082
DH	181	1	5	4.29	0.795
NL	181	1	5	3.91	0.908
PL	181	1	5	3.95	0.926
KCC	181	1	5	2.15	0.843
Valid N (listwise)	181				

Source: SPSS results.

In general, we see that the average value of the factors ranges from 2.15 to 4.29, which shows that the people surveyed evaluate the influence of the factors: compatibility, technical complexity. Techniques, business orientation, human resources, legal framework and market uncertainty all affect the adoptionof NLP to commercial banks in Vietnam.

Among these, the business orientation factor (DH) has the highest average level of 4.29. The standard deviation of this factor is 0.795. This reflects the opinions of the survey group's subjects who highly appreciated the influence of business orientation on the adoptionof NLP in commercial banks in Vietnam. The next level of influence is compatibility (TT), legal corridor (PL), human resources (NL), technical complexity (PT) and market uncertainty with an average level according to the order is 3.99, 3.95, 3.91, 2.25, 2.15.

5.2. Evaluate the Scale with Cronbach's Alpha

After the team analyzed the information obtained from SPSS, the research team checked the reliability of the data.

Table 2. Test results of the scale.

Factor		Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Compatibility			
TT1	a=0.876,N=4	0.746	0.836
TT2		0.816	0.807
TT3		0.720	0.847
TT4		0.655	0.870
Technical Complexity			
PT1	a=0.899,N=4	0.818	0.854
PT2		0.791	0.864
PT3		0.771	0.872
PT4		0.724	0.888
Bank Orientation			
DH1	a=0.895,N=5	0.683	0.885
DH2		0.724	0.876
DH3		0.770	0.865
DH4		0.765	0.867
DH5		0.769	0.866
Human Resources			
NL1	a=0.901,N=4	0.742	0.886
NL2		0.827	0.855
NL3		0.821	0.857
NL4		0.731	0.890
Legal Corridor			
PL1	a=0.930,N=3	0.877	0.882
PL2		0.897	0.864
PL3		0.799	0.882
Market Uncertainty			
KCC1	a=0.955,N=5	0.818	0.954
KCC2		0.880	0.944
KCC3		0.889	0.942
KCC4		0.889	0.942
KCC5		0.902	0.940

Source: SPSS results.

Using Cronbach's Alpha coefficient from the analysis results of SPSS software, we see:

- All 4 observed variables of the Compatibility factor meet the standards;
- All 4 observed variables of the Technical Complexity factor meet the standard;
- All 5 observed variables of the Business Orientation factor meet the standards;
- All 4 observed variables of the Human Resources factor meet the standards;
- All 3 observed variables of the Legal Corridor factor meet the standards;
- All 5 observed variables of the Market Uncertainty factor meet the standards.

By testing the appropriateness of the EFA factor analysis model, the research team relied on the KMO test and the Bartlett test to conclude that using the EFA model is appropriate. At the same time, the scale is also accepted through the results of testing the variance of the factors.

5.3. Analyze Regression Models

Using multivariate regression analysis techniques and the method of entering variables into SPSS software, results from the software have helped the research team evaluate some issues of the overall regression model:

$$UDCN = \beta_0 + \beta_1 TT + \beta_2 PT + \beta_3 DH + \beta_4 NL + \beta_5 PL + \beta_6 KCC$$

The important parameter used in testing model fit is the adjusted R^2 coefficient. The larger the value of this parameter shows the higher the model's fit.

After considering the effects of the independent variable on the dependent variable, the results from the regression weight table helped the research team determine the variables PT, DH, PL and (Constant) variables that are statistically significant and variable. NL, KCC and PT have no impact on the dependent variable UDCN.

Table 3. Results of regression.

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	2.961	0.470		6.300	0.000
	NL	-0.091	0.067	-0.128	-1.361	0.175
	KCC	0.082	0.092	0.083	0.887	0.376
	DH	0.200	0.081	0.225	2.474	0.014
	PT	-0.278	0.098	-0.320	-2.845	0.005
	PL	0.246	0.073	0.308	3.372	0.001
	TT	0.004	0.097	0.004	0.039	0.969

Source: SPSS results.

From there, the regression equation is determined:

UDCN = 2.961 - 0.278*PT + 0.200*DH + 0.264*PL

5.4. Discuss Research Results

The results of research and evaluation show that the process of applying natural language processing technology in commercial banks in Vietnam is influenced by different factors in terms of both external and internal impacts of businesses, directly impacting the adoption of this technology more widely.

From the initial hypothesis of 06 variables affecting the adoption of natural language processing technology in commercial banks in Vietnam, the results after running multivariate regression showed that only 03 variables recorded an impact, expressed in the formal regression equation as follows:

UDCN = 2.961 - 0.278*PT + 0.200*DH + 0.264*PL

According to the results after running the regression model, Hypotheses H2, H3 and H5 are accepted while the remaining 3 hypotheses including H1, H4, H5 are rejected. The research team assessed the levels of influencing factors. The research results show that the factor has a negative impact on Technical Complexity (0.278), followed by the remaining two factors that have a positive impact, respectively: the Legal Corridor factor (0.264) and the Factor Business Orientation factor (0.200).

In the 21st century, the Industrial Revolution 4.0 has created leverage for comprehensive transformation in many fields, especially the financial sector. This digital transformation trend motivates and requires financial organizations and businesses to adapt to new challenges and opportunities. This improved the quality of banks' operating processes, but many limitations remain.

According to the research results, the limitations in applying natural language processing (NLP) in commercial banks in Vietnam come from many factors, typically technical complexity. This technology not only requires an extremely complex structure of multiple entanglements and layers to operate, but also must be flexible in applying models corresponding to each specific task and field. This creates a challenging work environment, as experts need to deal with the possibility of algorithmic errors, which are sometimes only discovered when it is too late to fix them. Language diversity is also another problem to be faced, especially when NLP is not yet widespread enough in Vietnam to have enough data and analysis techniques. In addition, rapid change and growth, along with requirements for information security in data banks, also pose more challenges for experts in operating and developing NLP systems with depends significantly on the input data.

6. Recommendations

As outlined in the research context, the digital landscape in the financial sector requires significant collaboration among stakeholders, where the most affected entities are the banks and related businesses - the main actors in applying NLP to daily processes; and the regulatory authorities - entities that provide policies, support with the necessary conditions, and build an environment for implementation. Additionally, the support of scientists and researchers is crucial in applying NLP artificial intelligence technology to banking activities during the digital transformation period.

6.1. Recommendations for Regulatory Authorities

Regulatory bodies should issue specific policies and guidelines on the adoption of NLP in banking, while ensuring coherence and uniformity within the industry. Additionally, it is essential to organize training on NLP and its applications for bank officials and staff, and then encourage investment in the research and development of this technology. Regulatory authorities also need to support and encourage banks to implement NLP by creating a favorable environment with tax incentives and financial support, while regularly monitoring and evaluating the use of NLP in banks to ensure compliance with regulations and make adjustments when necessary. Furthermore, it is crucial to ensure transparency and fairness in the use of NLP to avoid creating inequalities among banks and to protect the rights of customers using related services.

6.2. Recommendations for Banks and Related Enterprises

Banks need to enhance internal communication to staff about integrating new technologies, not only NLP but also other technology platforms. Organizing workshops and training on NLP can help improve staff awareness and understanding of this technology, thereby recognizing its potential and opportunities, and minimizing concerns related to adopting new technologies.

Banks can drive digital transformation by integrating NLP and similar technologies, creating better customer experiences and offering automated services. This approach helps attract and retain customers, increase sales, and create a competitive edge. Additionally, researching NLP in conjunction with other technologies such as artificial intelligence and Blockchain allows banks to develop advanced, flexible solutions, and create differentiation in an increasingly competitive banking market.

6.3. Recommendations for Scientists and Researchers

Building a database and resources for NLP research must ensure accuracy, credibility, and diversity. Therefore, scientists and researchers need to continually update information and monitor new trends in the banking and technology sectors to maintain effectiveness.

Intensifying research and development of NLP solutions is essential, seeking practical applications with high potential in the banking sector such as automated translation, customer request processing, and data analysis to enhance service quality. Collaboration between entities and businesses also plays a critical role in this process. Moreover, information security, privacy, and legal compliance are vital considerations. Enhancing awareness of cybersecurity risks, establishing secure processing protocols, and implementing appropriate data security measures are necessary to ensure the sustainable development of NLP technology. Adhering to professional ethics and avoiding copyright infringement are also crucial in the research and adoption of NLP.

7. Conclusion

NLP is a technology with wide-ranging potential adoptions in commercial banks, bringing many benefits to both the banks and customers. The research study utilized quantitative and qualitative research methods, along with theories such as TRA, TPB, UTAUT, and TAM models, to propose solutions for banks to effectively implement this artificial intelligence tool. Additionally, the research study is an important first step in the research process, ensuring the accuracy and applicability of the research in practice.

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