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Thinking of How to Inspire Individuals to Use Smart Banking: Application of Big Data in the Banking Sector

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ABSTRACT: The paper utilizes a quantitative approach that is rooted in big data in the banking sector to identify the determinants that influence the decision of individuals toward online savings deposit decision-making. Accordingly, the dataset of 224,419 rows, equivalent to 52,400 consumers employed in the study. The research findings indicate that online savings deposits are dependent upon the duration of service engagement; those who have recently engaged in the service exhibit greater interest in online savings deposits. Clients with long-term deposits are likely to show interest in online savings deposits. Customers exhibit significant interest in deposit interest rates. Online savings deposits attract customers with higher deposit amounts and more assets. Nevertheless, clients with substantial deposit amounts, including wealthy clients such as Private and Premier Elite customers, typically refrain from utilizing online deposit services. Conversely, both regular and loyal clients exhibit a greater interest in online deposits. It is noteworthy that female clients have a greater preference for online deposit services compared to their male counterparts. The results indicate that younger clients are more inclined to select online savings deposits for deposit services compared to older customers.

KEYWORDS: Online savings deposit, length of stay, term deposit, savings term

1. INTRODUCTION

Capital mobilization is a fundamental operation and is almost the first to develop in the commercial banking system, playing an especially important role as the service that accounts for the main proportion and generates the principal profit for banks, particularly savings capital from individual customers, which has always been a top priority for commercial banks. Recently, capital mobilization has become more diverse, including both online and offline channels. This change cannot be mentioned without referring to the transformation of the digital technology system. It is the consequence that has led to the development of smart business in the banking sector.

Seemly significant changes in behavior of people happen after the COVID-19 pandemic. Therefore, the habit of using digital banking through websites or mobile apps for all activities and services of traditional banks has become more widespread and is growing at an extraordinary pace. Digital transformation and the adoption of digital banking are now among the core strategies helping banks optimize operational efficiency, simplify management and operational processes, reduce operating costs, and enhance user experience. As a result, banks are also able to optimize revenue and profitability.

The study of customer behavior toward making online savings deposits through the system will be based on big data from a bank currently operating in Ho Chi Minh City, Vietnam. Due to confidentiality requirements, the bank’s name will be kept anonymous and referred to as Bank XYZ. According to the internal report of Bank XYZ, the growth rate of individual customers using digital banking services (SmartBanking) has shown a declining trend and is reaching an alarming level. Currently, the proportion of online savings at Bank XYZ accounts for less than 35% of total deposits, compared to the industry average of 50%. On a national scale, the rate of online capital mobilization from individual customer accounts for less than 7%. This shift in the practical context also serves as one of the key motivations for developing the conceptual foundation of this study, ultimately guiding the construction of the proposed research model. The methodology employed in this study is based on a quantitative approach, utilizing big data sourced from Bank XYZ to identify the key factors influencing individual customers' decisions to engage in online savings deposit services. The research findings not only help measure the behavior of individual customers participating in online savings deposit services, as well as contribute to the theory of individual consumer behavior in using smart online system services in banking transactions but also serve as useful information contributing to the idea of how to exploit and absorb customer participation in online deposit services when conducting deposit transactions.

The next section of the paper will present an overview and a summary of the literature review. The following section will outline the research methodology. Next is the presentation of the data analysis results, and finally, the discussion of findings with proposed recommendations.

2. LITERATURE REVIEW

The development of Internet services and technologies has affected the operations and management of most commercial and non-commercial systems, including banking services (Singh et al., 2022), while traditional banking services are limited to physical channels such as bank branches, telephone banking, and automated teller machines (ATMs), Mobile Banking has eliminated physical constraints from daily banking activities. Customers can now complete their banking transactions at a time and place of their choosing (Srivastava & Gopalkrishnan, 2015).

Mobile banking, also called m-banking, is considered a form of digital banking (Kingshott et al., 2018). It is also considered a subset of mobile commerce (Singh et al., 2022) and an extension of e-commerce. Mobile banking is an application provided by government institutions or banks that allows users to perform remote political transactions by means of a mobile device such as a Personal Digital Assistant (PDA) or a smartphone. The banking application is downloaded and deployed to carry out payments such as checking bank accounts, executing transactions, and transferring money (Memon et al., 2017; Sharma et al., 2019). Mobile banking is considered a service with profit potential for both financial institutions and telecommunications organizations (Kingshott et al., 2018). As a commercial application characterized by mobility and wide reach, it has developed as a global phenomenon with promising feature improvements. In addition, mobile banking allows users to connect to the network at any time and conduct transactions simultaneously, and this has changed the uses of banking services (Sharma et al., 2019). This new technology has significantly reduced financial expenditure compared to traditional banking services.

For retail banks, mobile banking is not only beneficial for significantly reducing labor costs, and reducing the number of traditional bank branches (Kingshott et al., 2018) but also collects data on users' banking habits, which is very important for targeting and customization purposes. Mobile banking is also considered an alternative to conventional traditional channels to reach the global unbanked population.

Big Data in the banking sector

a. The development of the banking industry coincides with the emergence of Big Data

The banking industry has undergone a quantum leap over the past decade, spanning operational activities and service delivery. Remarkably, the majority of banks encounter difficulties or outright fail in utilizing and extracting information and data from the databases they have accumulated from customers and from their organizational branches and departments (Sharma et al., 2019). However, as banks increasingly extend their services and amenities or integrate technology to develop market segmentation and attract additional customers, they must concurrently establish an infrastructural framework for data collection, conduct analyses, and identify solutions to enhance business efficiency (Pérez-Martín et al., 2018).

There exists a multitude of Big Data sources across most industries and sectors, not only finance, commerce, retail, and insurance, but it is also of great interest in the banking sector. Every customer interaction and transaction within a bank generates electronic records and backups retained under legal requirements, and transactions conducted at ATMs in disparate locations likewise result in data being stored by the banking institution (Sharma et al., 2019). Thanks to big data analytics, financial services companies no longer store data solely to satisfy obligatory requirements as they did in the past; rather, they are now more active and proactive in exploiting it to achieve outcomes upon which solutions can be formulated to improve operations and augment organizational profitability.

Additionally, companies no longer wait for protracted intervals before analyzing historical or retrospective data. The majority of big data analyses are conducted principally in real time to expedite strategic decision-making (Pérez-Martín et al., 2018).

b. Altering the modalities of service delivery to customers

The Big Data system may constitute a complex apparatus interlinking multiple functional departments, yet its role is to simplify tasks within an organization. Whenever a customer name or account number is entered into the system, the Big Data infrastructure facilitates the screening of all data and selectively transmits or provides the requisite information for analytic processes. This capability enables banks to optimize their operational workflows and conserve both time and costs (Sharma et al., 2019). Big Data will also enable organizations to identify and rectify issues before they affect their customers.

Sometimes, customers may also constitute the source of a problem. For instance, investors may make decisions but subsequently alter their intentions at a future juncture. Big Data will assist banks in modifying their service-delivery methodologies in such a manner that customers will be unable to renegotiate on their initial commitments. Big Data enables the banking sector to monitor customers' loan and credit-card thresholds, ensuring that they do not incur expenditures beyond the prescribed limits

(Pérez-Martín et al., 2018). The manner in which service delivery is altered remains contingent upon the operational scale, the distinctive characteristics of the service modality, the infrastructure, and so forth, of that banking institution.

One of the most significant issues that the banking sector faces is fraud and crime in credit. Big Data will enable banks to ensure that no unauthorized transactions are executed, provide a heightened level of security, and elevate the security standards of the entire industry (Sharma et al., 2019).

By virtue of data regarding customers' transaction histories and credit dossiers, banks will be able to detect or receive alerts should any anomalies arise in the course of operational processes and service provision to clientele (Sun et al., 2014).

In addition to detecting criminal conduct and safeguarding consumer interests, banks may deploy Big Data to quantify and mitigate risk in equity transactions with investors and to scrutinize customers' loan dossiers. Naturally, all such activities must be predicated on analytically derived insights from the full corpus of pertinent historical data. Big Data algorithms further facilitate compliance with accounting, auditing, and transparent financial-reporting regulations, thereby rationalizing institutional operations and reducing managerial expenditures (Memon et al., 2017).

The study by Baten et al. (2009) utilizes the Stochastic Frontier Model to measure the efficiency of online deposits at banks. The research employs Maximum Likelihood Estimation to estimate the parameters of the stochastic profit frontier model, analyzes banks' efficiency in maximizing deposits, and concurrently computes the degree of inefficiency and the factors influencing that efficiency. Meanwhile, Hamadi & Awdeh (2012) concentrate on utilizing the Stochastic Frontier Analysis (SFA) model to measure banking efficiency. This study is not directly related to deposits but is concerned with the operational efficiency of banks in employing resources to maximize profit. Although it does not delve into detailed analysis of deposits, factors such as bank size, equity capital, and interest rates may indirectly affect deposit management and banks' profitability efficiency.

Zaki et al. (2024) focus their study on the application of predictive analytics and machine learning in banks' direct marketing strategies, particularly in predicting term deposit subscriptions. The primary objective of the research is the utilization of machine learning models to enhance the efficiency of banks' marketing strategies, aiming to optimize customer acquisition for term deposit products. In addition, machine learning models, namely the SGD Classifier, K-nearest Neighbor (KNN), and Random Forest were applied to analyze customer data and predict the propensity of clients to subscribe to term deposits.

3. RESEARCH METHOD AND MODEL

The data employed in this research originates from the Big Data repository of Bank XYZ. These data were extracted from the institution's data warehouse. The temporal scope of the dataset corresponds to each day's transactions conducted by customers at Bank XYZ. The total number of transaction lines spans from January 1, 2024, to December 31, 2024, equivalent to 12 months, comprising 161,904 pertaining to 32,676 customers, which implies that each customer executed multiple transactions during the study interval.

Customers incorporated in the study must have maintained deposit-service engagement for a minimum of six months. Omitting those with tenures below six months serves to constrain the information noise that might compromise data reliability.

Although many variables are stored within the Big Data source, this study will approach the ten variables as indicated in Table 1. Each variable possesses different measurement values, which include continuous, ordinal, and nominal.

Table 1: Variable and its measure

No	Variable	Definition	Measure
	Length of stay	The length of stay as tenures is determined from the date of the client's activation.	Continuous (month)
	Term deposit of client ranked	The savings term is the time customers deposit money at the bank and are committed to receiving interest rates according to regulations.	Ordinal variable: (divided into group: 1= General customer group; 2 = loyal customer group; 3= Premier customer group; 4 = Premier Elite customer group; 5= Private customer group)
	Total deposit	Deposit amount to receive interest rate	Continuous (VND)*
	Interest rate	Interest rate that the customer gets from its deposit	Continuous (percentage)
	Savings term	A term of saving categorizes various durations (e.g. short-term, medium-term, long-term).	Ordinal variable: (divided into group: 1 = short term; 2= medium term; 3= long term)
	Balance of client	Balance of client engaged in banking services	Continuous (VND)

	Asset of client	The value of customers' assets is recorded by the bank when participating in the service.	Continuous (VND)
	Gender	Gender of individual customer	Nominal variable where 1 represents male and 0 represents female
	Age	Age of individual customer	Continuous (age in years)
	Online savings deposit	Defined as a service of online saving deposit of individual.	The dummy variable is defined as 1 if an online savings deposit has been made, and 0 otherwise.

Note: VND = Vietnamese Dong; 1 USD = 24,335 VND

The selection of variables for inclusion in the estimation, as aforementioned, is predicated on previously published research.

Length of stay (LOS): a continuous variable measured in months. The measurement is computed from the date on which the customer activated participation in the deposit service at Bank XYZ until the date of the study. The inclusion of LOS is grounded in the explanatory approach of Mohammed et al. (2023) and Saharon et al. (2003). According to these authors, a longer customer tenure in the service yields greater contributory value to a business entity.

Term deposit of client ranked (TD): the fixed-term period for which an individual deposits funds with the bank. Deposit tenors vary, ranging from several weeks to months, years, and sometimes include non-term arrangements. For analytical clarity, Bank XYZ stratifies depositors into five tiers, ranked from lowest to highest: 1 = General customer category; 2 = Loyal customer category; 3 = Premier high-end customer category; 4 = Premier Elite high-end customer category; 5 = Private high-end customer category. The adoption of this variable in the model follows the explanatory reasoning of Zaki et al. (2024).

Interest rate (IR): Deposit interest is the percentage of profit that a bank or financial institution pays on a customer's deposit over a specified interval. This is the interest that depositors receive when depositing money into savings products such as savings books, term or non-term deposit accounts. Deposit interest is usually calculated annually (%/year) and may change according to the bank's policy, as well as the general economic situation of the market. According to Baten & Kamil (2011), deposit terms serve as an incentive mechanism for customer acquisition and retention by the bank.

Saving term of deposit (ST): Upon deposit placement, customers are assigned to a deposit-tier classification. ST is categorized into three groups: 1= non-term, 2= short-term, and 3= long-term. The adoption of this variable in the model follows explanatory reasoning. According to Zoric (2016), the ranking and segmentation of customers enable the bank to formulate appropriate strategies to stimulate service utilization and banking transactional activity.

Balance of client (BC): It constitutes the remaining monetary amount in an individual's or organization's account at a specific point in time. The balance may fluctuate continuously due to deposit or withdrawal transactions. The unit of measurement for the balance is a continuous value denominated in Vietnamese dong. This variable is referenced based on the study of Hany & Alaa (2013).

Asset of client (AC): the total asset value declared by the customer upon service enrollment, measured in Vietnamese dong. According to Hamadi & Awdeh (2012), asset of a client relates to the client's transactional engagement at the bank

Gender (GE): denotes the gender of the individual customer, classified in this study into male and female cohorts. According to Covin et al. (2020), gender exerts a determinative influence on decision-making. From this perspective, customer gender is incorporated into the research model as a control variable.

Age (AG): denotes the individual customer's age, calculated from the customer's year of birth at the point of service activation. Age exerts an influence on developmental trajectories. According to Akman & Mishra (2010), age is related to individual behavior when making a decision.

Online savings deposit (OSD): This is the dependent variable, the unit of measurement for this dependent variable is a dummy variable, with 1 = customer subscribes to the online deposit service, and 0 = customer does not subscribe to the online deposit service. The reference of this variable is based on the explanatory reasoning of Baten & Kamil (2011) and Hany & Alaa (2013).

The consolidated information on the variables used in the model is summarized in Table 2.

Table 2: Variables and their definition

No.	Variable name	Authors
	LOS: Length of stay of client (months)	(Mohammed et al., 2023), (Saharon et al., 2003)

	TD: Term deposit of clients ranked (divided into group: 1= General customer group; 2 = loyal customer group; 3= Premier customer group; 4 = Premier Elite customer group; 5= Private customer group)	Zaki et al. (2024)
	TO: Total deposit (Converted to logarithm)	Zaki et al. (2024)
	IR: Interest rate (Percentage)	(Baten & Kamil, 2011)
	ST: Savings term class (divided into group: 1 = short term; 2= medium term; 3= long term)	(Zoric, 2016)
	BC: Balance of client (Converted to logarithm)	(Hany & Alaa, 2013)
	AC: Asset of customer (Converted to logarithm)	(Hamadi & Awdeh, 2012)
	GE: Gender (1 represents male and 0 represents female)	Covin et al. (2020)
	AG: Age (years old)	Akman & Mishra (2010)
	OSD: Online savings deposit (defined as Yes if an online savings deposit has been made, and otherwise being No)	(Baten & Kamil, 2011), (Hany & Alaa, 2013)

Relying on the measurement scales of the independent and dependent variables, the binary logistic regression model was applied to forecast behaviors influencing individual customers' decisions regarding online savings deposits. The variable of online savings deposit is dependent, while independent variables are LOS, TD, TO, IR, ST, BC, AC, GE, and AG. The software of KNIME is employed to test the model. Its result is presented in the next section.

4. EMPIRICAL ANALYSIS

The dataset included in this study comprises daily transactions from January 1 to December 31, 2024. There are 161,904 rows, each representing a client's transaction, equivalent to 32,676 individual customers of Bank YXZ.

The statistical results describe the proportion of customers participating in the service in the study, with male gender accounting for 46% and female accounting for 54%. The proportion shows a small difference. This result, in part, also shows the role of female participating in the deposit service.

As mentioned previous, five groups of ranked client with term deposit are concerned, which the general customer group accounts for 79%, next as the loyal customer group with 10%, next as the Premier group with 8%, the Premier Elite customer group with 2%, and the Private customer group with 1%, in which the Private customer group receives the best priority policies, next as the Premier Elite customer group, the Premier customer group, the loyal customer group, and the general customer group (without any priority).

The paper examines three categories of client saving terms as defined. Descriptive statistics indicate that 72% of the client group utilize online savings deposits as their short-term savings accounts. The client group that has medium-term and long-term online savings deposits comprises 27% and 1%, respectively.

Determinants of online savings deposits of clients

As defined previously, the number of customers in the study is customers who are depositing money at XYZ Bank. In terms of proportion, at the time of the study, 15% of the customer group participated in the online savings deposit service, and the remaining 85% were not participating in the online deposit service. In the data, the customer group participating in the online saving deposit service is encoded as "yes", and not participating in the online deposit service is encoded as "no". This coding will help the next step to determine the measurement value of the online saving deposit variable as a target variable.

To identify how the client thinks to decide its online saving deposit, the logistic regression model is employed. It is estimated through the software of "KNIME". The result of logistic model estimation is depicted in table 3, 4, and 5.

Testing the logistic model is processed through partitioning implementation. Partitioning refers to the process of dividing a dataset into distinct subsets or partitions. This can be useful in various contexts, such as in data analysis, where you might want to separate data for training and testing in machine learning, or in database management, where data is split across different storage locations for efficiency. In this paper, a practice is to use an 80/20 split, where 80% of the data is used for training the model, and the remaining 20% is reserved for testing the model's performance. This ensures that the model is trained on a substantial amount of data while still having a separate set of data to evaluate its accuracy and generalization.

As shown in Table 3, the model presents an overall accuracy of 91.09%. According to Landis & Koch (1977), the Cohen's kappa value of 0.647 concludes that the logistic model demonstrates substantial agreement.

Table 3: Scorer's view of testing the logistic regression model

Confusion Matrix

Rows Number : 32381	No (Predicted)	Yes (Predicted)	
No (Actual)	26152	1501	94.57%
Yes (Actual)	1383	3345	70.75%
	94.98%	69.03%	

Overall Statistics

Overall Accuracy	Overall Error	Cohen's kappa (κ)	Correctly Classified	Incorrectly Classified
91.09%	8.91%	0.647	29497	2884

Table 4: The result of logistic model estimation

Logistic regression	Independent variable	Coefficient	Standard error	Z-Score	P>|z|
No	Saving term	-6.252	0.095	-66.083	0.000
No	InterestRate	-2.421	0.057	-42.616	0.000
No	BalanceClient	0.772	0.290	2.661	0.008
No	LOS	8.657	0.244	35.492	0.000
No	AGE	6.318	0.098	64.789	0.000
No	ASSET	1.583	0.198	7.994	0.000
No	Total deposit	-1.312	0.222	-5.908	0.000
No	GENDER_G	0.116	0.025	4.714	0.000
No	Term deposit	0.939	0.051	18.438	0.000
No	Constant	1.185	0.049	23.984	0.000

Note: No = Clients without participating in the online saving deposit; Yes = Clients participating in the online saving deposit.

As mentioned previously, the proportion of clients without online savings deposit accounts for 85%, otherwise it is 15%. The result of the estimation depicted in the table is a presentation of the relationship between the "NO" decision of online savings deposit and the independent variables.

To length of state (LOS), its coefficient is positive (8.657) and significant at any level (P>|z|= 0.000). This concludes that customers who have a longer tenure do not consider the online savings deposit service. This may be because the habit of customers who have used the service for a long time always sticks to the traditional deposit method.

To term deposit (TD), its coefficient is positive (0.939) and significant at any level (P>|z|= 0.000). This concludes that clients with the high ranking, e.g. Premier customer group, Premier Elite customer group and Private customer group don't consider much the online saving deposit service. This means that clients with the ranking of general customer group and loyal customer group pay more attention to the online saving deposits.

To total deposit (TO), its coefficient is negative (-1.312) and significant at any level (P>|z|= 0.000). This concludes that the higher total deposits, the higher consideration of the online savings deposit. This is an important message, customers with larger deposits at the bank pay attention to online savings deposits, maybe they have faith in the bank's services, and do not want to spend a lot of time participating in deposit services.

To interest rate (IR), its coefficient is negative (-2.421) and significant at any level (P>|z|= 0.000). The results conclude that the higher the interest rate, the more consideration of client on online saving deposit. This is completely consistent with practice because customers always expect higher interest rates and will be more inclined towards online deposits.

To saving term (ST), its coefficient is negative (-6.252) and significant at any level (P>|z|= 0.000). This concludes that the deposit class of individual customers affects the online deposit of customers. Accordingly, once the term of deposit is longer the online saving deposit is more concerned.

To balance of client (BC), it has a positive coefficient (0.772) and significance at 1% level (P>|z|= 0.008). The balance shown in the account of individual customers exists not to choose an online money deposit service. This means once the balance of clients increases, it does not have a tendency to care about choosing an online money deposit service.

To assets of client (AC), its coefficient is positive (1.583) and significant at any level (P>|z|= 0.000). Accordingly, AC exhibits greater propensity of customers with large assets not selecting the online deposit service. This finding provides crucial information for the bank to leverage the people with high assets toward the online savings deposit.

To gender (GE), it exhibits a positive coefficient (0.166) with a significant level at any level (P>|z|= 0.000). This allows the conclusion that individual customer gender does influence the choice of the online deposit service. As previously defined (1 = male; 0 = female), in which female customer segments are more inclined than males to select the online savings deposit service. This aligns with empirical observation, since women often play a central role in money management and saving, and thus female customers will seize the opportunity to deposit online to safeguard their existing funds.

To age (AG), it exhibits a positive coefficient (6.318) with significant at any level. This outcome allows the conclusion that age significantly influences the choice of deposit service. Given the positive, as individual customer age increases, the likelihood of selecting the online deposit service decreases. In other words, younger customers display a greater propensity to opt for the online deposit service. This finding aligns, to some extent, with empirical observation, since younger cohorts are generally more technologically proficient, routinely update information, and capitalize on the benefits offered by banking services.

5. CONCLUSION

The research utilizes an analytical methodology based on the bank's Big Data repository. The research sample consists of 32,676 individual clients, with 54% identified as female and 46% as male. The results demonstrate that participation in online deposits is dependent on service tenure: consumers with more recent involvement show increased interest in online deposits. Individuals with extended deposit tenors also exhibit a preference for online saving deposit services. Customers exhibit significant sensitivity to deposit interest rates. Furthermore, the adoption of online saving deposits is more prevalent among clients with substantial account amounts and significant asset holdings. Customers in the highest deposit categories, namely the Private and Premier Elite segments, generally do not utilize the online deposit service. Conversely, the general and loyal customer sectors exhibit a greater propensity for online savings deposits. Female clients exhibit a greater propensity than male customers to utilize the online saving deposit service. The findings indicate that younger customers are more inclined than older cohorts to choose online saving deposits at the time-of-service activation. Building on these insights, the following section of the thesis will present recommendations for strategic development.

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