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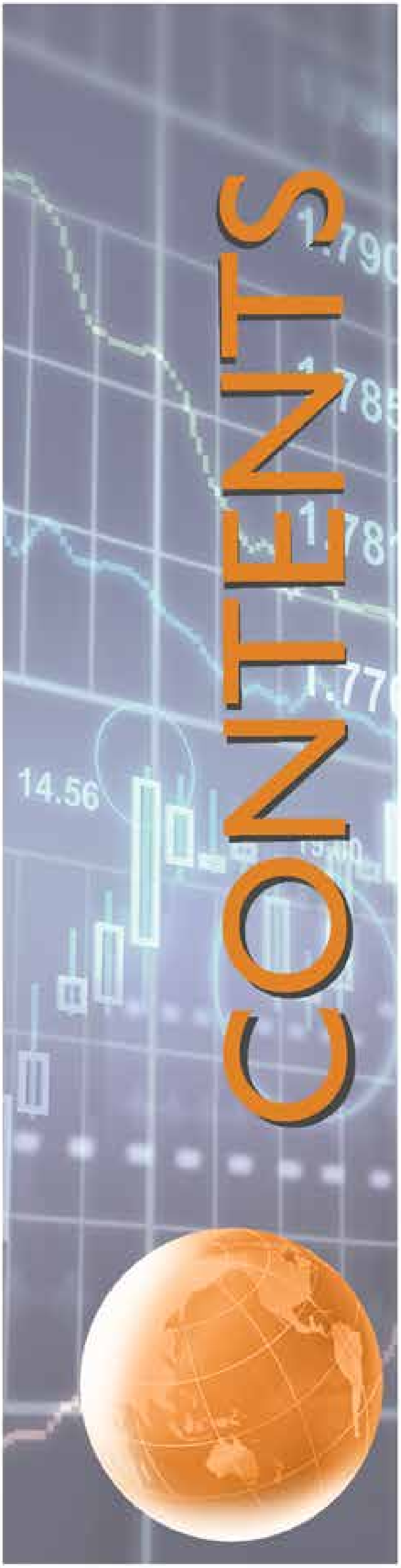

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PRIORITISATION OF FACTORS FOR ARTIFICIAL INTELLIGENCE-BASED TECHNOLOGY ADOPTION BY BANKING CUSTOMERS IN INDIA: EVIDENCE USING THE DEMATEL APPROACH

SWARAJ S BHARTI[1], KANIKA PRASAD[1], SHWATI SUDHA[1], VINEETA KUMARI[2*]

1. National Institute of Technology Jamshedpur, India
2. Magadh University, Bodh Gaya, India

* Corresponding Author: Name, Dept, University, City, Country ✉ email address

Abstract

Artificial Intelligence (AI) is a concept of recent origin and is accepted for banking activities such as customer service, detection of fraudulent activities, and suspicious transactions. For the successful implementation of AI in the Indian context, a deep understanding is required in terms of its need and importance compared to the traditional banking system. To date, this outlook of AI has been less focused by industry practitioners and experts for the smooth flow of operational procedures in banks for developing countries, for example, India. This study aims to unearth factors and establish a relationship among the identified factors through the decision-making trial and evaluation laboratory (DEMATEL) approach to categorize the factors and frame the cause-and-effect relationships. Fifteen factors are identified through a literature review of existing studies, and ten experts were solicited to express their outlook on this subject within a period of six months. The result indicated that 'Transparency of information,' 'Perceived security of AI-based technology,' 'Social influence on customer,' 'Government regulation of AI in banks,' 'Awareness level of AI,' 'Efficiency of AI system,' 'Technical requirement,' and 'Cost of AI-based technology' were causative factors that support customer acceptance and penetration of AI in banks. The study presents a unique approach to customer acceptability towards AI in banks in developing countries using the DEMATEL technique. This study also discusses the possible area for the adaption of AI in Indian banks. The findings will support policymakers and practitioners in executing AI-based technologies in the banking sector in emerging nations.

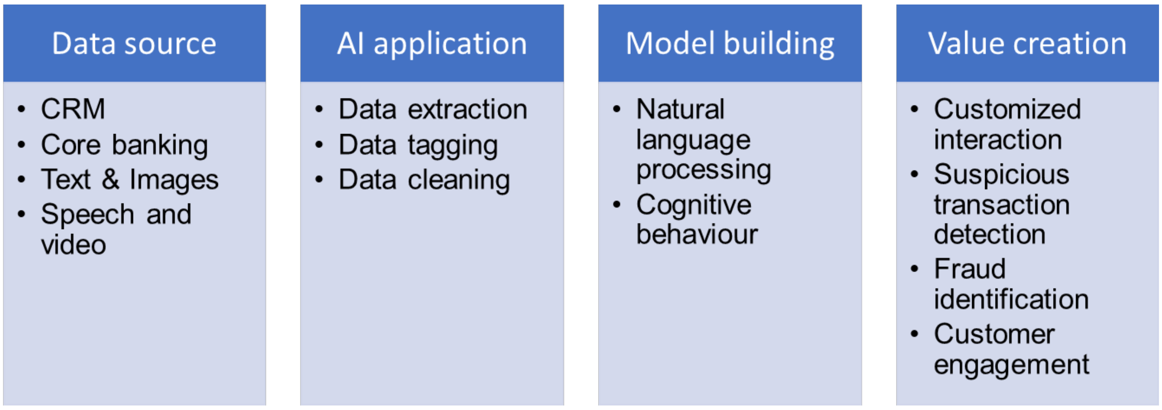
Keywords: DEMATEL; bank customers; artificial intelligence; Customer adaptation; India

1. Introduction

In today's world, Artificial Intelligence (AI) is considered one of the most promising technologies for customer service that incorporates algorithms, language, machine learning, etc (Wang et al., 2021; Rodrigues et al., 2022). AI tries to mimic human behaviour and intelligence to learn, think, and act similarly to gain insights about individuals' perceptions and predict future actions (Yadav, 2021). In the future, AI technology will be commercialized in other sectors, such as E-commerce, healthcare, supply chain, and disaster management (Singh and Srivastava, 2018). The AI system incorporates the Natural language of humans for understanding and generating responses for customer interaction in banks (Buchanan and Wright, 2021). Integration of customer services with AI technology would benefit the banking sector, where the customer database is extensive, and analysis of these data is required precisely and accurately. The requirement of services for financial investment for customers and improving those areas for customer retention can be fulfilled by AI very efficiently (Tao et al., 2021).

Additionally, if the customer is satisfied with the response rate and the queries are resolved satisfactorily, then the trust factor is multiplied. Adopting these AI-based technologies could reduce the cost of accessibility of credit facilities for lenders and borrowers. Moreover, this significantly decreases the risk of fraudulent activities and the customer's financial loss. The cyber security risk and the privacy concerns of the user can be addressed through the use of AI in order to maintain financial stability at banks. It is used in social media analytics to scan banking-related data and develop a model for predicting future product demands. The AI-based system can detect financial fraud in banks, thus making the system more secure and safe (Li et al., 2021; Pourhabibi et al., 2020). Figure 1 describes the process adopted by AI for providing customer service in banks with different layers of sourcing, application, building, and delivery. Customer query response time is a crucial factor in banks' performance and support in customer acquisition. Chatbot, an AI-enabled technology, is extensively used in banks for customer service and relationship management are tested with cognitive capabilities to improve the service and interaction process in India. However, other areas, such as operation, authentication, and payment system, require automation in India. So, the demand for AI in banks will increase in India. The process of determination of credit worthiness of banking customers can be done through the predictive models of AI. Rapid improvements in the digital divide can be initiated with the emergence of AI technology in the banking and financial sector. AI system is employed on non-traditional data such as patterns of social media usage, internet browsing history, and Global Positioning System (GPS) records for locations to analyse the demand of the banking customer (Meghani, 2020).

Figure 1: Process of AI-Enabled Technology in Customer Service at Banks



Notes: CRM: Customer relationship management

AI's acceleration rate in recent years has proved that automation is the future of banking. Banks' futuristic scope lies in employing the Banking-as-a-Service (BaaS) platform for developing an ecosystem focusing on a data-centric approach. It can reap significant benefits for the long-term goal of the business and assist in growth. A robust digital base can be developed through AI-enabled technologies for database management, such as storage, cleaning, and categorizing the profile of the customers accordingly (Pu et al., 2021). So, AI implementation in the future requires understanding the vital factors, and the banking authorities must know which areas need more attention than others. Moreover, the service industry's competitive environment allows customers to switch from one bank to another easily. This study will highlight the retention part from the implementation and customer retention sense. The former banking channels concentrated on cross-channel interaction with the customers; however, customer demands have significantly changed the intuitive, customized, and omnichannel experience (Chakravaram et al., 2021). The personalized engagements of customers for attaining financial objectives are the key to customer satisfaction and loyalty which can be easily performed by AI (Kant and Jaiswal, 2017). The extant literature also focused on the advantages of AI and the dependencies related to it. These are significant in studying the acceptability and hence implementing it in future.

It is evident from the above discussion that customers' experience will be amplified to a more significant extent with the inclusion of AI in customer interaction and banking services. The present study seeks to contribute to the banking domain by evaluating the importance of AI in customer service interaction and identifying fraudulent activities. Although Indian banks are yet to adopt AI, extant literature based on this study found numerous uses of AI-enabled technology in banking operations worldwide (Milana and Ashta, 2021; Ahmed, 2021). The problems arising out of AI execution in banks necessitate the need to study the factors that influence the adaptation behaviour of the customer (Ryzhkova et al., 2020). Therefore, in this paper, to measure the extent of acceptability of AI in Indian banking services, the driving factors for adopting AI-based technology are studied in detail and subsequently ranked according to their importance from the customers' perspective. This will bring innovation in customer service in the banking industry and guide the policymakers to frame appropriate fundamentals related to AI. The factors are prioritized based on their importance and their interdependence on each other. The relatedness of the drivers serves the purpose of a specific application of AI in banks, which can be resolved through a multi-criteria decision-making (MCDM) tool (R et al., 2021; Černevičienė et al., 2022). The nature of the problem reveals that the data and information provided are unpredictable. Hence, the decision-making trial and evaluation laboratory (DEMATEL) technique is applied for ranking the factors using peer comparison and derivation of a causal diagram for understanding. It visualizes the qualitative judgments of the expert's opinions and existing literature into a clearly defined rational structure. The study's findings pave the way for policymakers and bankers to introduce AI in their systems, keeping in mind the significance of factors as per the result obtained in this study. Overall, the end user, i.e., customers, will be able to adapt to the technology efficiently and benefit in the long run. For this process, several factors were considered that promote AI usage in banks, and those factors were segregated into cause and effect using the DEMATEL method.

The rest of the paper is as follows: Section 2 provides a brief literature review, Section 3 discusses the research gap and objectives, Section 4 describes the research methodology, Section 5 discusses the findings, Section 6 concludes the study, and Section 7 discusses a few practical implications, limitations, and scope for future research.

2. Review of Literature

The previous literature provides ample scope and possibilities of AI in banks and how it can reshape the banking environment in the future. The emergence of Fintech companies which are handling large volumes of data and utilizing those data to study customer behaviour and expenditure pattern, creates their own identity in the financial industry apart from banks (Milian et al., 2019; Gomber et al., 2018). According to Sharma and Sharma (2019), the most financial transaction takes place via mobile phone, which changes the traditional mode of communication to an advanced application in banking. However, more than mobile banking is needed to utilise more resources or ideas to capture, store, segregate, and utilize data for determining customers' perceptions (Shareef et al., 2018; Chawla and Joshi, 2017). The introduction of newer technologies in the banking industry is a two-way process, where the customer acceptability of the technology is of utmost importance (Alalwan et al., 2018; Asadi et al., 2017). The various technologies introduced in Turkish, Chinese, and Persian banks have been mentioned in Table I for reference. None have applied the F-DEMATEL technique to AI implementation in the Indian banking industry. Although many drivers were undertaken for the research conducted by (Humbani and Wiese, 2018), convenience and compatibility with online payment services were of utmost importance (Lin et al., 2020; Shaikh et al., 2020). The marketing of AI dramatically depends on the quality of users, the development of the country, and the scope of operation by industry (Kopalle et al., 2021; Chen et al., 2021; Wang et al., 2021). AI-based technology facilitates automation in the service industry, and the customer feels they are in charge of the decisions more than the physical approach (Subero-Navarro et al., 2022; Khatib, 2021; Königstorfer and Thalmann, 2020). The significant advantage of AI in banks is personalized customer interaction, cost reduction, and opportunities for establishing recent business models to compete in the market (Joshi and Ranjan, 2021; Kaur et al., 2020; R et al., 2021). Additionally, AI will have a significant role in extracting data and applying analytics to provide the required results (Luna et al., 2019; He et al., 2021). Virtual assistant such as chatbots in bank facilitates customer relationship management, reduction of workload, and saves time (Kumar et al., 2018; El-Gohary et al., 2021; Muthukannan et al., 2020). Ibrahim and Nwobilor (2020) and Tang and Tien (2020) highlighted the ease of complicated data handling of customers through AI-enabled technologies in banks. It also provides opportunities for decision-making during banking operations and customer service in Indian banks (Sepehri-Rad et al., 2019; Maheswaran and Benaka Santhosh, 2021; Anagnostopoulos, 2018). The present study employs the DEMATEL technique to identify factors necessary for establishing AI-enabled technology in banking. The suitability of the research methodology is governed by studying different studies conducted using similar techniques in several countries' banking and financial arena (Gupta et al., 2022; Rahman et al., 2021). Table I gives a detailed description of the information study according to similar research methodology applied in different banking industries. The extant study unearths factors necessary for implementing AI related to customer service in a finite way. Hence, the present study focuses on the crucial factors for AI implementation in the banking environment from the perspective of customer acceptability.

Table 1: Tabular Elaboration of Similar Research Methodology Applied in Different Sectors

S no.	Area of application of AI	Description	Methodology	Author(s)
1.	E-commerce	Evaluation of the authentication process in online banking at Parsian Bank	DEMATEL	Sepehri-Rad *et al.*, 2019
2.	Indian banking industry	Success factors for evaluation of E-service quality	Analytical Hierarchical process (AHP)– Technique for order performance by similarity to ideal solution) TOPSIS–DEMATEL approach	Agrawal *et al.*, 2020
3.	Safety and Risk analysis	Risk factors and sources of information	DEMATEL with Best Worst method and Bayesian network (BN)	Yazdi *et al.*, 2020
4.	E-commerce	Identification and prioritization of factors	Interpretive structural modelling (ISM) and fuzzy analytical process	Valmohammadi and Dashti, 2016
5.	European Banking Sector	Analysis of Incremental and Disruptive Innovation Policies	DEMATEL, TOPSIS, VIKOR	Dincer *et al.*, 2019
6.	Banking industry	Determine criteria for selection of location for new bank branches	Fuzzy-DEMATEL	Vafadarnikjoo *et al.*, 2015
7.	Behavioural psychology	Addiction to social media	DEMATEL	Dalvi-Esfahani *et al.*, 2019
8.	European banking sector	Evaluation of concentration and competition of different places in Europe	Fuzzy DEMATEL, fuzzy ANP, and fuzzy VIKOR	Dincer *et al.*, 2020
9.	Turkish banking sector	Comparison of financial performance of Turkish banks	DEMATEL, Grey Relational Analysis (GRA) and MOORA approach	Yüksel *et al.*, 2017
10.	Banking industry	Factors responsible for adoption of internet banking	DEMATEL-ANP-SEM approach	Lin *et al.*, 2020

S no.	Area of application of AI	Description	Methodology	Author(s)
11.	European banking industry	Evaluation of investment in Fintech	Fuzzy DEMATEL, Fuzzy TOPSIS, and Fuzzy VIKOR	Kou *et al.*, 2021
12.	Business analytics	Human resource selection in an organization	DEMATEL and Elimination and Choice Expressing the Reality (ELECTRE)	Kilic *et al.*, 2020
13.	Banking industry	Factors responsible for information technology outsourcing in banks	Fuzzy-DEMATEL	Gerami and Feili, 2016
14.	Chinese banking industry	Factors for improvement of financial innovation in banks	F-DEMATEL, Analytic network process (ANP), and VIKOR approach	Zhao *et al.*, 2019
15.	Manufacturing industry	Investor perception for selection of industry	Fuzzy hybrid Analytical model	Dincer *et al.*, 2016

Notes: This table provides a summary of extant literature to which this study contributes.

3. Research Gap and Objectives

The current research study revealed the utilization of AI-based technology in different fields for customer service interaction and handling of operational procedures in the organization. The extant literature focused on the utilization of AI, the implications of AI in a marketing sense, and its primary benefit in the service industry. Although AI is replacing tasks that are mundane and repetitive. However, the research study conducted formerly provides data that is uncertain in nature and inconsistent in banks. Few researchers have focused on the customer acceptability of AI-based technologies in banks in developing countries such as India. To bridge this gap, the present study employs the Fuzzy-DEMATEL approach to remove vagueness and thoroughly evaluate the factors influencing the use of AI-based technology in the banking industry. The extant literature addresses the factors necessary for establishing AI-enabled technologies in banking from the perspective of customer acceptability in a limited manner. The concept of addressing the drivers related to customer acceptability that influence the practice of AI in banking that incorporates the Fuzzy-DEMATEL technique is novel. This assessment of the factors will play a crucial role in determining its futuristic implication for banking customers and pave the way for successful implementation by policymakers.

This study sets out to find the relative association among the factors and resolution of entangled issues related to AI-enabled technology in banks through an impact relation graph. The primary objectives of this research study are as follows:

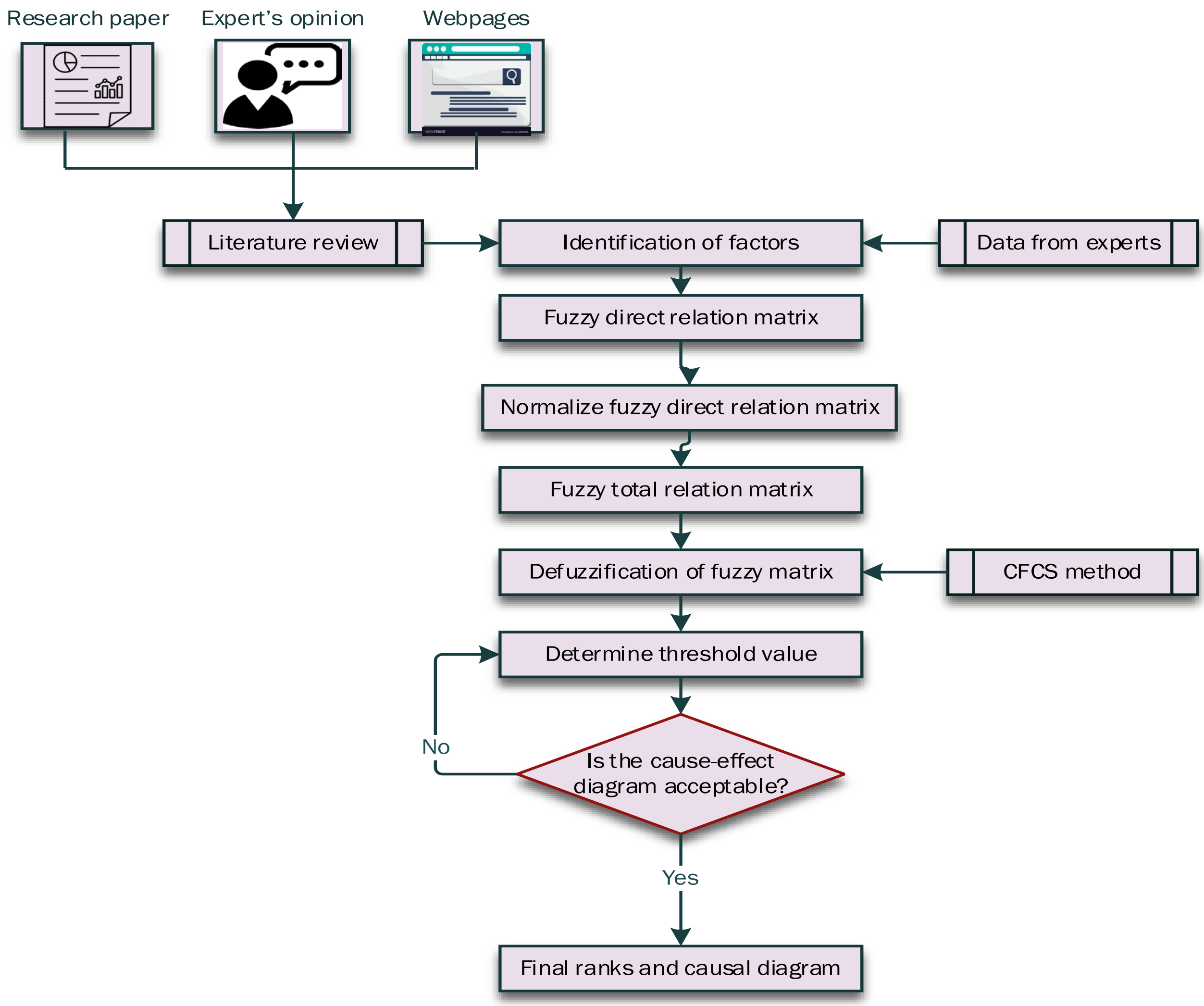
a) Identification of factors for AI-enabled technology adoption by banking customers
b) Rank the factors crucial for AI-enabled technology adoption according to their importance
c) Analyse cause and effect relationship among the factor that determine AI-enabled technology adoption

4. Research Methodology

To address the objectives mentioned above, the factors were determined using the existing studies and supplicate input from the experts in the Indian banking industry. The cause-and-effect relationship was determined using a decision-making trial and evaluation laboratory (DEMATEL). The factors considered are independent of each other from the theoretical perspective. However, each factor is interdependent on the other in real life. This inter-relatedness is evaluated well by the

DEMATEL technique and specifies the extent of the influence of one factor on the other. Evaluating the correlation of the drivers of AI-enabled technology in banks through DEMATEL is most appropriate for prioritizing the factors according to their importance. Moreover, this technique clearly distinguishes the cause-and-effect drivers from the factors for problem measurement. This technique is widely used in various industries worldwide, such as manufacturing (Shavarani et al., 2018; Dincer et al., 2016), medical (Longoni et al., 2019), supply chain (Chang et al., 2011), and e-commerce (Chiu et al., 2014; Sepehri-Rad et al., 2019) to address and prioritize the influence of the factors based on peer comparison method. The results further assist the clear directions and importance of the selected factors during evaluation. Figure 2 illustrates the DEMATEL technique.

Figure 2: Framework for the Current Study



Notes: The figure depicts the research flow of the study, starting from the source of data collected and analysis of the results obtained.

4.1 Survey Instrument

In a practical sense, the expert opinion in the case of DEMATEL tends to be qualitative with the use of linguistic terms. Hence, the technique utilizes fuzzy set theory to convert these qualitative values into a crisp form. The questionnaire was disseminated to the intended experts through e-mail, and the response was collected through the same medium. The Likert scale was used for filling up the responses starting from 0-4, where 0 means "Very low impact" and 4 means "Very high impact." Altogether, ten experts were selected, i.e., five from the banking domain and five from the academic domain, to express their views on this subject. All the experts possess more than five years of work experience in their respective domains. The experts from the banking domain include the Product manager, the Head of the banking and operation department in the retail banks, the Head of customer service and operations, the Business head, and the Cluster head. There were Associate professors, Professors, and Dean (research and consultancy) from the academic domain.

The Cronbach Alpha of the self-designed questionnaire was 0.86, indicating the high reliability of the questions asked. The value of Cronbach alpha lies between 0 to 1, where 0 signifies no reliability and 1 indicates the highest reliability. Usually, a reliability of more than 0.7 is considered apt for a research study (Prentice and Nguyen, 2021; Sepehri-Rad et al., 2019).

4.2. Flow of Methodology Adopted

Step 1: Identification of factors responsible for customer adoption of AI-based technology in the banking sector.

The factors were determined through a literature survey obtained from published research articles and conference proceedings extracted from different databases, including Scopus and Web of Science. The basis of the selection of the research paper was recency and relevancy with the topic. The experts were solicited for validation of those identified factors, and the purposive sampling technique was applied to select experts in the domain. Two sub-factors were eliminated after consultation with the experts as they were not significantly related to AI-based technology, and lastly, 15 sub-factors were considered important for the study. The factors were categorized into cognitive and mental behaviour, cultural and educational, risk and performance, and external aspects according to the significance of the AI-based technology. Table 2 elaborates the description of each factor in the context of AI-enabled banking technology.

Step 2: Construction of fuzzy direct relation matrix.

An 'n × n' matrix is created to compute the relationship among the factors given. A fuzzy number represents the influence of the element present in each row on the elements present in each column. Every expert input for further calculation must complete the fuzzy matrix. Lastly, the arithmetic mean of every expert's opinion is used to construct the direct relationship matrix termed as stated in Equation 1.

$$a = \begin{bmatrix} 0 & \cdots & \tilde{\mathrm{a}}_{n1} \\ \vdots & \ddots & \vdots \\ \tilde{\mathrm{a}}_{1n} & \cdots & 0 \end{bmatrix} \tag{1}$$

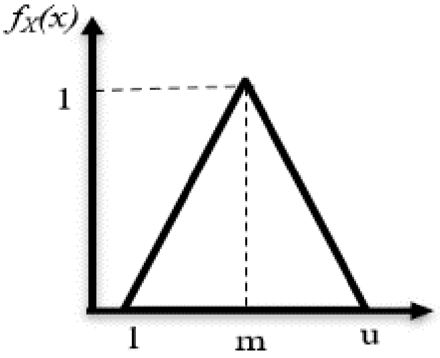
For each element present column-wise, the matrix columns are divided into three parts representing *l*, *m*, and *u*. Since triangular fuzzy scales are used, the values of each input from 0-4 can be referred to from Table 3. Every member of the fuzzy set contains a degree of membership and a membership function. The membership function has a real number starting from zero to one. The triangular membership function is the most commonly used, having three values: *l*, *m*, and *u*. The triplet (*l,m,u*) where $l \leq m \leq u$ indicates the smallest, medium, and largest probable values, respectively. Figure 3 highlights the triangular membership function used in the fuzzy set.

Table 2: Brief Description of the Drivers that impact Artificial Intelligence in Indian banks

Factors	Sub-factors	Notation	Description	Source
Cognitive and mental behaviour	Perceived trust	D1	The degree to which customers perceive that AI technology is better than human interaction	Shareef *et al.,* 2018; Sharma and Sharma, 2019
	Social influence on customer	D2	The effect of social interaction and the flow of information among various generations of people determines the popularity of technology	Sivathanu *et al,* 2019; Alalwan *et al.,* 2018
	Attitude of customers toward AI	D3	Perceived cognitive and effective behavioral aspect; intention to use the service	Luna *et al.,* 2019; Mehrad and Mohammadi, 2017
Cultural and education	Awareness level of AI	D4	The extent to which customer believes that AI learn enough information, including consciousness	Hassija and Srivastava, 2020; Sabharwal, 2018
	Information quality	D5	Nature and variety of information provided	Qadiri *et al.,* 2020; Shareef *et al.,* 2018
	Ease of use	D6	Utility and functional benefit to the customer; effortless, simple to learn, and use	Luna *et al.,* 2019; Humbani and Wiese, 2018; Johnson *et al.,* 2018
Risk and performance	Security of AI system	D7	The extent to which customer is ready to reveal personal and financial information during AI-enabled interaction devoid of misuse.	Sepehri-Rad *et al.,* 2019; Shareef *et al.,* 2018; R. and Ravi, 2021
	Efficiency of AI system	D8	Optimization of time and resources to produce quality service to a customer	Baabdullah *et al.,* 2019; Shareef *et al.,* 2018
	Transparency of information provided by AI	D9	Perceived openness of information from both ways	Joshi *et al.,* 2021; Prentice and Nguyen, 2021
	Satisfaction of customer	D10	The extent of fulfilment of customers' expectations and providing contentment	Karjaluoto, *et al.,* 2019; Arcand *et al.,* 2017; Asadi *et al.,* 2017
	Responsiveness	D11	Faster communication	Vafadarnikjoo *et al.,* 2015; Ravikumar *et al.,* 2021
External aspects	Government regulation of AI in banks	D12	The degree to which the laws and regulation has a controlling effect on the AI	Raj and Sah, 2019; Ramamurty *et al.,* 2021
	Perceived environmental consideration	D13	The impact of AI technology on the environment and global development	Truby *et al.,* 2020; Raj and Sah, 2019; Mhlanga, 2020
	Technical requirement	D14	Includes innovativeness and flexibility for the customer	Sepehri-Rad *et al.,* 2019; Raj and Sah, 2019; Karjaluoto, *et al.,* 2018
	Cost of AI technology	D15	Evaluation of price comparison with human interaction	Alalwan *et al.,* 2018; Ryu, 2018; Alzaidi, 2018

Note: The drivers are derived from existing literature studies and are used for prioritization of the factors accordingly.

Figure 3: Triangular Membership Function



Note: The triangular membership function has three values: l, m, and u. The triplet (l,m,u) where l$\leq m \leq u$ indicates the smallest, medium, and largest probable values.

Table 3 gives the linguistic scales used for the triangular fuzzy membership function. We provide the direct relation matrix (X_{n*n}) through the pairwise comparison of the values presented in the matrix given by the experts in Appendix A1.

Table 3: Fuzzy Scales

Fuzzy Code	Linguistic scales	L	M	U
0	No influence	0	0	0.25
1	Very low influence	0	0.25	0.5
2	Low influence	0.25	0.5	0.75
3	High influence	0.5	0.75	1
4	Very high influence	0.75	1	1

Note: The experts were given these linguistic scales for responses in a tabular fashion. The values in the responses have the linguistic scale accordingly.

Step 3: Normalize the fuzzy direct relation matrix.

The normalized fuzzy direct-relation matrix is computed by using the following formula given in Equation 2:

$$\tilde{x}_{ij} = \frac{\tilde{a}_{ij}}{k} = \left(\frac{l_{ij}}{k}, \frac{m_{ij}}{k}, \frac{u_{ij}}{k}\right) \tag{2}$$

where, the value of k is determined by Equation 3, and *i* and *j* vary from 1 to n.

$$k = \max_{i,j}\left\{\max_{i} \sum_{j=1}^{n} u_{ij}, \max_{j} \sum_{i=1}^{n} u_{ij}\right\} \qquad i,j \in \{1,2,3,\dots,n\} \tag{3}$$

Step 4: Calculation of fuzzy total-relation matrix.

The fuzzy total-relation matrix is obtained through the following formula in step 4, and the value of Z is generated by equation 4:

$$\tilde{Z} = \lim_{r \to +\infty} (\tilde{x}^1 \oplus \tilde{x}^2 \oplus \ldots \oplus \tilde{x}^k) \tag{4}$$

Assuming that if every element of the fuzzy total-relation matrix is represented as $\tilde{p}_{ij} = (l^{"}_{ij}, m^{"}_{ij}, u^{"}_{ij}$, it is calculated as follows in the subsequent Equations 5, 6, and 7.

$$[l^{"}_{ij}] = x_l \times (I - x_l)^{-1} \tag{5}$$

$$[m^{"}_{ij}] = x_m \times (I - x_m)^{-1} \tag{6}$$

$$[u^{"}_{ij}] = x_u \times (I - x_u)^{-1} \tag{7}$$

To illustrate, the inverse of the normalized matrix is computed firstly, and secondly, it is subtracted from matrix I, and lastly, the normalized matrix is multiplied by the resulting matrix.

Step 5: Defuzzification of the fuzzy matrix into crisp values

Cheng and Hwang introduced Converting Fuzzy data into Crisp Scores (CFCS) method in 1992 to uncomplicate some of the steps in DEMATEL. The resulting fuzzy scores are converted to crisp values using a technique similar to that used to calculate the left and right scores using fuzzy minimum and fuzzy maximum, respectively, and the total score is calculated using the membership functions as a weighted average. The alternatives are calculated according to the *i*^th^ criteria with fuzzy numbers. The steps of the CFCS method are as follows:

$$l^n_{ij} = \frac{\left(l^p_{ij} - \min l^p_{ij}\right)}{\Delta^{max}_{min}} \tag{8}$$

$$m^n_{ij} = \frac{(m^p_{ij} - min\ l^p_{ij})}{\Delta^{max}_{min}} \tag{9}$$

$$u^n_{ij} = \frac{(u^p_{ij} - min\ l^p_{ij})}{\Delta^{max}_{min}} \tag{10}$$

So that,

$$\Delta^{max}_{min} = \max u^p_{ij} - \min l^p_{ij} \tag{11}$$

Computation of the upper and lower bounds of normalized values known as fuzzy min and fuzzy max

$$l_{ij}^{t} = {m_{ij}^{n}}\Big/{(1 + m_{ij}^{n} - l_{ij}^{n})} \tag{12}$$

$$u_{ij}^{t} = {u_{ij}^{n}}\Big/{\left(1 + u_{ij}^{n} - l_{ij}^{n}\right)} \tag{13}$$

Determining the total normalized crisp values, which is a weighted average according to the membership functions

$$x_{ij} = \frac{[l_{ij}^{t}(1 - l_{ij}^{t}) + u_{ij}^{t} \times u_{ij}^{t}]}{[1 - l_{ij}^{t} + u_{ij}^{t}]} \tag{14}$$

The result of the CFCS algorithm is crisp values as given in Table 4, and the calculations are expressed from Equations 8-14 mentioned above.

Table 4: Crisp Values of the Fuzzy Numbers Obtained

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15
D1	0.1890	0.2117	0.2384	0.2054	0.2162	0.2230	0.2029	0.2091	0.2198	0.2398	0.2407	0.2152	0.2204	0.2237	0.1922
D2	0.2346	0.1783	0.2371	0.2434	0.2299	0.2219	0.2396	0.2235	0.2201	0.2106	0.2109	0.2292	0.2030	0.2211	0.1905
D3	0.2327	0.2098	0.1888	0.2419	0.2122	0.2043	0.2364	0.2219	0.2015	0.2234	0.2088	0.2402	0.2187	0.2351	0.1899
D4	0.1953	0.2214	0.2476	0.2093	0.2540	0.2323	0.1907	0.2179	0.2286	0.2352	0.2216	0.2507	0.2122	0.2480	0.2457
D5	0.2214	0.1966	0.2056	0.2143	0.1699	0.1772	0.2377	0.1928	0.2049	0.2125	0.2259	0.1821	0.1727	0.2067	0.2070
D6	0.1922	0.1860	0.2268	0.2188	0.2062	0.1643	0.2285	0.2139	0.2087	0.1994	0.2159	0.2189	0.1769	0.2280	0.2270
D7	0.2264	0.2180	0.1970	0.2040	0.2341	0.1972	0.1826	0.1989	0.1955	0.2168	0.2028	0.2191	0.2103	0.2118	0.1828
D8	0.2088	0.2352	0.2462	0.2534	0.2391	0.2146	0.2325	0.1845	0.2266	0.2464	0.2348	0.2372	0.2267	0.2311	0.2310
D9	0.2274	0.2095	0.2151	0.2067	0.2082	0.2165	0.2316	0.2012	0.1646	0.2189	0.2042	0.2062	0.1963	0.2099	0.1843
D10	0.2498	0.2255	0.2527	0.2598	0.2449	0.2054	0.2384	0.2495	0.2316	0.1929	0.2536	0.2276	0.2440	0.2525	0.2376
D11	0.2318	0.2085	0.2349	0.2415	0.2287	0.2039	0.2063	0.2046	0.1842	0.2065	0.2156	0.2256	0.1999	0.2474	0.2209
D12	0.2092	0.2189	0.2076	0.2191	0.1891	0.1968	0.2280	0.2136	0.1924	0.1835	0.1992	0.1717	0.2225	0.2271	0.2127
D13	0.2376	0.2297	0.2272	0.2035	0.1884	0.2210	0.2121	0.1970	0.1763	0.2184	0.1991	0.2185	0.1600	0.2258	0.2111
D14	0.1835	0.2077	0.2311	0.2247	0.2127	0.2044	0.1885	0.1890	0.2148	0.1748	0.2211	0.1788	0.1818	0.1698	0.2181
D15	0.2264	0.2179	0.2036	0.2135	0.2375	0.2152	0.2319	0.2297	0.1809	0.2023	0.2237	0.2048	0.1778	0.2285	0.1675

Note: The crisp values have been obtained after using a technique similar to that used to calculate the left and right scores using fuzzy minimum and fuzzy maximum, respectively, and the total score is calculated using the membership functions as a weighted average.

Step 6: Determine the threshold value.

The threshold value is determined to calculate the total internal relations matrix. It is adequate to compute the average values of matrix T to determine the threshold value for relations. After determining the threshold intensity, the values present in the matrix T, which are lesser than the threshold value, are set to zero. Accordingly, the threshold value is equal to 0.075471698 in this study. Hence, all the values in matrix T, which are smaller than 0.075471698, are set to zero; that is, the causal relation is not considered. The values greater than 0.075471698 are set to one. The result obtained after computing the threshold value is mentioned in Table 5.

Table 5: The Crisp Total- Relationships Matrix by Considering the Threshold Value

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15
D1	0	0	1	0	1	1	0	0	1	1	1	1	1	1	0
D2	1	0	1	1	1	1	1	1	1	0	0	1	0	1	0
D3	1	0	0	1	0	0	1	1	0	1	0	1	1	1	0
D4	0	1	1	0	1	1	0	1	1	1	1	1	0	1	1
D5	1	0	0	1	0	0	1	0	0	0	1	0	0	0	0
D6	0	0	1	1	0	0	1	0	0	0	1	1	0	1	1
D7	1	1	0	0	1	0	0	0	0	1	0	1	0	0	0
D8	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1
D9	1	0	1	0	0	1	1	0	0	1	0	0	0	0	0
D10	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1
D11	1	0	1	1	1	0	0	0	0	0	1	1	0	1	1
D12	0	1	0	1	0	0	1	0	0	0	0	0	1	1	0
D13	1	1	1	0	0	1	0	0	0	1	0	1	0	1	0
D14	0	0	1	1	0	0	0	0	1	0	1	0	0	0	1
D15	1	1	0	0	1	1	1	1	0	0	1	0	0	1	0

Note: The threshold value is equal to 0.075471698 in this study. All values in matrix T, which are smaller than 0.075471698, are set to zero; that is, the causal relation is not considered. The values greater than 0.075471698 are set to one.

Step 7: Determine the final output and construct a causal relation diagram.

The final output is obtained by calculating the sum of each row and each column of T (in step 4). The sum of rows is expressed as C, and the sum of columns is expressed as R, which are calculated as per Equations 15 and 16:

$$C = \sum_{j=1}^{n} T_{ij} \tag{15}$$

$$R = \sum_{i=1}^{n} T_{ij} \tag{16}$$

Table 6: Final Output of the Fuzzy Matrix

	C	R	C+R	C-R	Horizontal vector rank of C+R	Vertical vector rank of C-R
D1	3.2476	3.266	6.5136	-0.0183	6	10
D2	3.2935	3.1746	6.4681	0.1189*	7	3
D3	3.2656	3.3596	6.6252	-0.0941	3	11
D4	3.4104	3.3592	6.7697	0.0512*	1	5
D5	3.0274	3.2712	6.2986	-0.2438	11	14
D6	3.1115	3.0979	6.2094	0.0136*	13	8
D7	3.0973	3.2878	6.385	-0.1905	8	13
D8	3.4482	3.1471	6.5953	0.3010*	4	2
D9	3.1005	3.0507	6.1513	0.0498*	14	6
D10	3.5656	3.1813	6.7469	0.3843*	2	1
D11	3.2602	3.2779	6.5382	-0.0177	5	9
D12	3.0914	3.2256	6.3171	-0.1342	10	12
D13	3.1258	3.0233	6.1491	0.1025*	15	4
D14	3.0007	3.3665	6.3672	-0.3657	9	15
D15	3.1612	3.1183	6.2795	0.0430*	12	7

*Notes: * indicate the causal factors. C+R represents the degree of importance of factor i in the entire system, and C-R represents the net influence of factor i that contributes to the system.*

Then, the values of C+R and C-R are calculated using the given values of C, and R. C+ R is called prominence, whereas C-R is called relation. C+R represents the degree of importance of factor *i* in the entire system, and C-R represents the net influence of factor *i* that contributes to the system. Table 6 shows the final output.

Figure 4 presents the model of significant relations of the factors where the values of (C+R) is arranged on the horizontal axis, and the values of (C-R) is arranged on the vertical axis. Figure 5 states the graphical visualization of the overall research process.

Figure 4: Causal Diagram of the Result Obtained

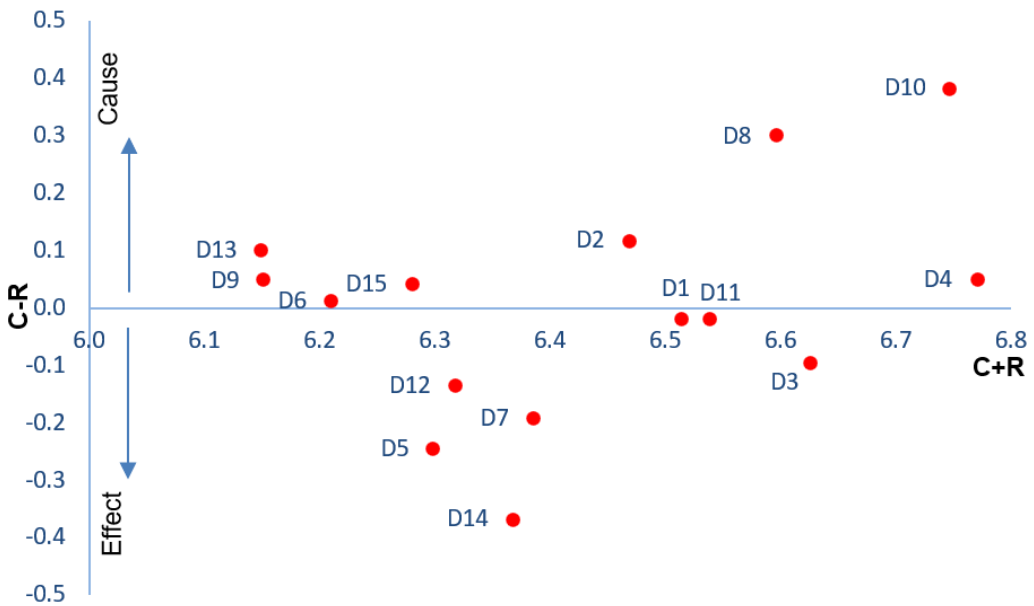
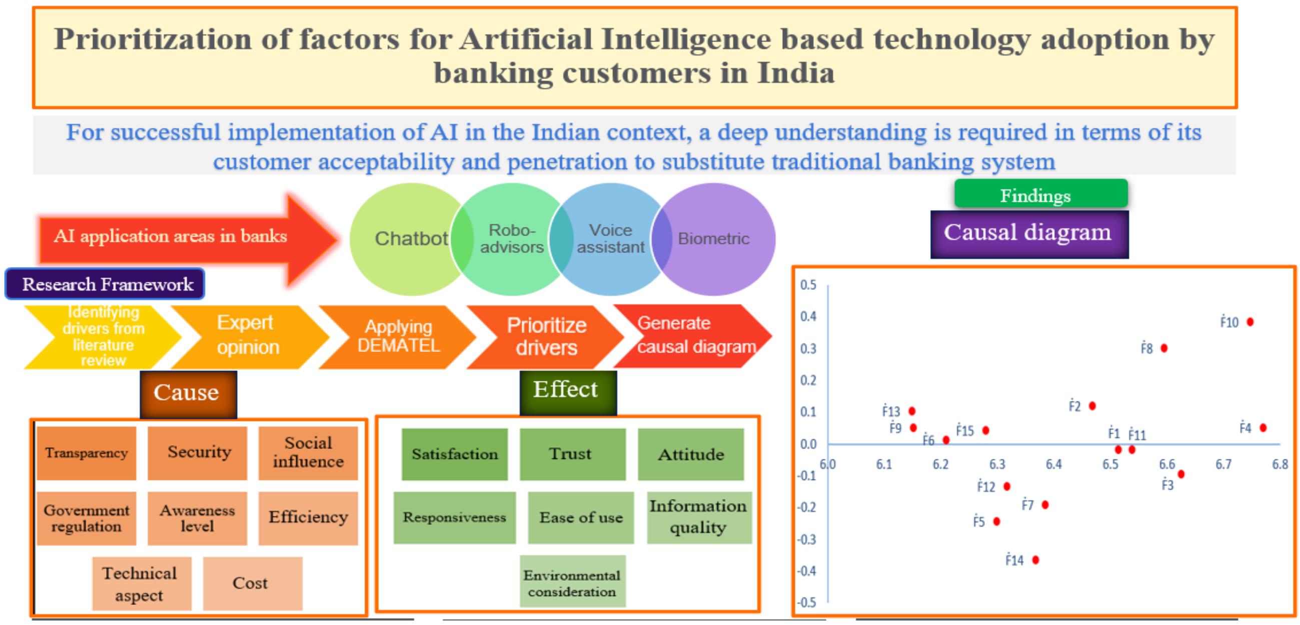


Figure 5: Graphical Visualization of the Research Process



5. Findings and Discussion

The categorization of the sub-factors leads to a greater understanding of the influence in a proportionate direction with the help of a digraph. The factors are divided into cause-and-effect groups based on the result. The cause group comes from (C-R>0), and the effect group comes from (C-R<0), and a causal diagram is mapped. The causing factor influences the entire system, and their execution affects the study's overall objective. Table 7 clearly shows the factors divided into cause and effect according to the result obtained. The results are in line with the former literature conducted in this field.

Table 7: Differentiation of Factors into Cause and Effect of AI-based Technology in the Banking Sector

S No.	Causal factors	S No.	Effectual factors
1	Transparency of information provided by AI (D9)	1	Satisfaction of customer (D10)
2	Security of AI system (D7)	2	Perceived trust (D1)
3	Social influence on customer (D2)	3	Attitude of customer towards AI (D3)
4	Government regulation of AI in banks (D12)	4	Responsiveness (D11)
5	Awareness level of AI (D4)	5	Ease of use (D6)
6	Efficiency of AI system (D8)	6	Information quality (D5)
7	Technical requirement (D14)	7	Perceived environmental consideration (D13)
8	Cost of AI technology (D15)		

Note: The factors are classified into cause and effect according to the result obtained.

The study analysed the customer acceptability towards AI-enabled technologies in Indian banks through the application of MCDM methodology. Based on the results obtained through DEMATEL analysis, the factors are arranged according to the extent of the measured impact on AI. The final values of eight causal and seven effect factors are presented in Table 7. The cause factors are transparency of information provided by AI (0.0498), security of AI-enabled system (0.3010), social influence on customers (0.1189), government regulation of AI in banks (0.1025), the awareness level of AI (0.0512), the efficiency of AI system (0.0498), the technical requirement (0.0430), and cost of AI-enabled technology (0.0136). The effectual factors are the satisfaction of customers (-0.0177), perceived trust (-0.0183), the attitude of customers towards AI (-0.0941), responsiveness (-0.1342), ease of use (-0.1905), information quality (-0.2438), and lastly perceived environmental consideration (-0.3657). In other words, it can be framed as D9>D7>D2>D12>D4>D8>D14>D15>D10>D1>D3>D11> D6>D5>D13. The ranking of different factors is discussed in detail.

5.1. Discussion on Major Causal Factors

This analysis reveals that the banking authorities and decision-makers in the financial industry should focus more on the transparency of information provided by AI-enabled technologies. Therefore, the sub-factor 'transparency of information provided by AI-enabled system (D9)' under the factor risk and performance is the most crucial factor in determining its successful implementation in banks, according to the expert's opinion. Factor D9 has an influential impact on the other seven factors. Information transparency will be prevalent if the data fed into the AI system is complete and accurate (Joshi *et al*., 2021; Prentice and Nguyen, 2021).

The second most important sub-criteria is 'security of AI-based technologies (D7)' under the factor risk and performance. Apparently, due to rising cases of fraudulent activities, security is an important aspect the banks must work upon. The breach of data and dissemination of unvalidated data can wrongly impact the relationship between the banks and their customers. The communication channel should be encrypted with security layers, and any trigger of failure should be communicated immediately (Sepehri-Rad *et al.*, 2019; Shareef *et al.*, 2018; R. and Ravi, 2021).

The third most vital sub-factor is 'social influence on the customer (D2)' under cognitive and mental behaviour. Nowadays, the bank's goodwill is also determined by the perception of its customers in respect of the latest technology used, and customers tend to distribute that information through social media and mass communication. This is why banks must be careful with their user's perceptions, and a continuous feedback system is encouraged for improvement (Sivathanu *et al.*, 2019; Alalwan *et al.*, 2018).

The fourth important sub-criteria is 'government regulation on AI in banks (D12)' under the criteria external factors. The governmental regulation on AI-based technology will determine the extent to which the customer can reap benefits from AI in banks in India (Raj and Sah, 2019; Ramamurty *et al*., 2021).

The fifth important sub-factor is the 'awareness level of AI (D4)' under cultural and educational factors. In case of low awareness, the banking sector needs to train its customers about the AI-enabled platform and its advantages over the traditional banking system (Hassija and Srivastava, 2020; Sabharwal, 2018).

Similarly, the subsequent factors were organized as 'efficiency of AI-based system (D8)' under the driver risk and performance at sixth position, 'technical requirement (D14)' under the factor external aspect at the seventh vital sub-factor, 'cost of AI-based technology (D15)' under the factor external aspect as the eight most important sub-factor.

5.2. Discussion on major effectual factors

The ninth principle sub-factor is 'satisfaction of customer (D10)' under the risk and performance is most affected due to several given causes above. Hence, customer satisfaction must be of prime importance for banking officials while implementing AI-based technology for customer relationships and operational processes (Karjaluoto *et al.*, 2019; Arcand *et al.*, 2017; Asadi *et al.*, 2017).

The tenth key sub-driver is 'perceived trust (D1)' under the drivers of cognitive and mental behavior. The trust factor is vital for the growth of AI-enabled systems where the customers are ready to experiment with different forms of banking interaction and verification processes, such as biometrics and iris scanners, in the future (Shareef *et al.*, 2018; Sharma and Sharma, 2019).

The eleventh significant sub-criteria is the 'attitude of the customers towards AI (D3)' under cognitive and mental behavior criteria. The demand for AI will be shaped by the attitude formed by the customers toward AI and the faster response of AI compared to the manual mode of interaction (Luna *et al.*, 2019; Mehrad and Mohammadi, 2017).

Subsequently, the other effectual factors are stated as 'responsiveness (D11)' under the criteria risk and performance as the twelfth sub-criteria. The thirteen crucial sub-driver is 'ease of use (D6)' under the cultural and educational drivers. The fourteenth vital sub-factor is 'information quality of AI (D5)' under cultural and educational factors. Lastly, under the external driver aspect, the fifteen significant sub-driver is 'perceived environmental consideration (D13)'. The prioritization of the drivers necessary for successfully implementing AI-based technologies in banks will assist in providing alternatives for executing recent technology. The banks will be able to reposition their focus to establish AI as a medium for customer communication and perform smooth operational procedures, as discussed in past studies. The effectual factors can be controlled to provide favorable results to meet the banking sector's organizational goals in the future.

6. Conclusions

AI-based technologies have immense potential to change banks' traditional customer interaction and service scenarios through automated systems and technology. The best part about AI is that it positively contributes to environmental considerations for future and resource optimization. The stress on human resources may be reduced considerably due to the introduction of AI in fraud identification and detection of suspicious transactions of large volume by the customer through algorithmic architecture. The study's major objectives, such as identifying drivers, ranking of those drivers, and analysis of cause-and-effect drivers, are fulfilled through the literature review and expert opinion. The results of the DEMATEL technique state that driving factors significantly impact the practical application of the study undertaken. Additionally, this study's results emphasize the customer perception of the transparency of information provided by AI and the security features of AI in banks. Moreover, the causal factors directly influence customer satisfaction and trust in banks. Implementing AI is vital for the smooth flow of operations and requires planning with direction. The study guides those drivers crucial for the penetration of AI-based systems in Indian banks.

7. Practical Implications, limitations, and future research avenues

Since the concept of AI in banking is of recent origin in India, the results obtained in this study can be used as initial guidance to bear in mind the factors influencing AI incorporation in banks. The major objective of this paper is to provide a path for banking officials and regulators who are planning to encompass AI technology in their banking system in the future. Through adequate planning and clarification, the probability of success of implementation may be increased. The decision-makers working in this direction must focus on the perception of customers towards environmental consideration as well as the quality of the information provided by AI-based technology. Based on these factors and the acceptance rate in India, the financial regulatory agency (Reserve Bank of India) may focus on creating a digital penetration index. Due to the difficulty of quantifying the study's subjective factors, banks may create different scales of measurement compared to the customers' existing feedback systems. DEMATEL technique gives us clarity regarding the visualization of factors into fundamental (causal) and effect. Research practitioners who are applying the use of AI in banking may detect and identify their deprived areas through this study.

Future research studies may incorporate more than four factors and fifteen sub-factors for DEMATEL analysis. The output of the study is derived from the expert opinion related explicitly to AI-based banking systems, which cannot be generalized to other fields in banking. However, the results are fruitful for pursuing the scope of AI-enabled technologies in banking in the Indian scenario. It may be applied to different sectors or industries, such as manufacturing or telecommunication, dealing with the introduction of AI in their system to encourage an efficient result in the future. The technical complication can prove to be a major barrier to implementing successful AI-enabled technology in banks.

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STUDENT LOANS: LESSONS FROM BORROWERS

INGA TIMMERMAN[1], NIK VOLKOV[2]

1. University of North Florida, United States
2. Mercer University, United States

* Corresponding Author: Inga Timmerman, Assistant Professor, Accounting & Finance, Coggin College of Business, Office 42/3405, University of North Florida. * inga.timmerman@unf.edu

Abstract

The study presents the results and the analysis of a survey of recent student loan borrowers. The fields of study that result in the highest disbalance between the amount borrowed and the generated earnings are identified. Additionally, the survey results shed light on the post-graduation spending behaviour of the borrowers. The results indicate that the present student loan crisis may, at least in part, be caused by the selection of the major area of study and by the post-graduation personal consumption over adjustment of individuals from several (less financially lucrative) fields of study.

Keywords: Student Loans, Higher Education, Personal Consumption

JEL Classification: D14, D31

1. Introduction

The subject of the high cost of higher education and the "student loan crisis" has been at the forefront of media coverage and political debate in the United States over the last decade. The student loan forgiveness programs and the ideas of free college education have been frequently referenced as the solutions to the student loan crisis and means of providing equal educational opportunities to people of all socio-economic groups. As such, during the week of May 30, 2022, the Biden administration announced billions of dollars in automatic student loan forgiveness for over half a million borrowers. The program was further expanded on August 24, 2022. While arguing that student loans put significant financial pressure on vulnerable households, further support for the concept of loan forgiveness has been grounded in the argument that the economic benefit of obtaining higher education has been diminishing over time (see Forbes, September 25, 2020). Since then, the topic has been so politicised that it made it all the way to the US Supreme Court in June 2023, with the Court deciding against forgiveness and the three-year freeze on student loan payments is expected to expire by the end of 2023, with millions of borrowers being forced into resuming their payments.

Most of the media and academic coverage of the student loan crisis centres on the present problem instead of looking at the issue's underlying causes. There appears to be a lack of focus on the individual borrower's decision-making at the time of the borrowing. Furthermore, the financial decisions such borrowers make upon completing their higher education journey have not been thoroughly examined. In the current study, we look at the behaviour of individual borrowers and attempt to identify some commonalities that may shed light on the underlying causes of the crisis.

We explore the following questions: (1) when does taking student loans constitute a "good" (value-creating) financial decision, and (2) what specific decisions with respect to higher education-related borrowing result in outcomes that are viewed as positive by the borrowers? Our contribution is threefold. First, we identify additional factors that need to be incorporated into the student loan worthiness debate. As such, we find that two determinants primarily drive the *ex-post* perception toward student loans: (1) the choice of the field of study and (2) an increase in personal consumption upon Graduation. Second, we introduce the personal consumption adjustment element into the conversation. Despite its importance in the decision of when and how to take student loans, it is hardly mentioned in the literature and analysis on the topic. Finally, we offer the individual perspective rather than an aggregate view of the topic, which could further enhance the understanding of who and when should be taking on student loans.

According to the US government[1], students can borrow in different ways, ranging from $5,500 per year for Direct Subsidised Loans to $20,500 per year for Direct Unsubsidized graduate loans. Furthermore, according to the College Board, the total amount borrowed for post-secondary education was about 102 billion dollars in the 2019-2020 period. Despite what seems to be a very high number, it represents a decline in borrowing for the ninth consecutive year. The average number borrowed per student is around $28,800 based on the 2018–2019-year data, a relatively modest change from $26,600 in 2008-2009 (this level of change represents an 8 percent decline in borrowing on an inflation-adjusted basis). The trend report also points out that after reaching a peak in 2010-2011, the total borrowed amount has been declining. Additionally, the Board identifies that, as of March 2020, 55% of all borrowers with outstanding loans owed less than $20,000. On the other extreme, 45% of all outstanding debt was owed by 10% of borrowers who owed more than $80,000 each[2]. According to Forbes, the newest information on student loan borrowing puts the average borrower in 2023 at $28,950, with 55% of students attending a public and 57% of students attending a private nonprofit four-year institution with student loans[3].

Although average numbers are useful, it is hard to understand the specifics of the student loan issue by looking at the figures in the aggregate. Media reports about the rising cost of college continue building the impression that the problem is becoming larger. In 2019, student loan debt was second to mortgages, exceeding credit card and auto borrowing in aggregate dollars. About 15% of the US population had outstanding student loans. About 101.4 billion dollars of student loans were in default, a figure that represents about 11.4% of the total outstanding student loans. Major changes have been observed between 2020-2023 due to the student loan payment pause. As of 2022, the default rate dropped to 2.3%, its lowest in years[4]. Given the lengthy pause in payment expectations, the recent numbers are artificially deflated. With the Supreme Court decision in June 2023, the defaults are expected to spike again.

There appears to be a disconnect between the perception of how acute student loan borrowing is and the actual borrowing of a typical college graduate. As current and future students are faced with their own educational and education-related investment decisions, the tools and the information availability appear to be biased and skewed toward a specific group of borrowers, which paints a rather grim picture of student loans. In reality, however, a well-thought-through educational decision financed using student loans is more likely than not to be among the best investments an individual will make in his/her lifetime. Furthermore, the non-discriminatory access to student loans offers an excellent opportunity for underprivileged classes to reap the long-lasting rewards of having a higher education.

To shed light on the student loan issue and the origins thereof, we examine the ex-post perceptions toward student loans of individuals who utilised such loans in pursuit of their higher education. We conducted a survey of borrowers who graduated and are employed or seeking employment at the time of the survey. The individuals' pre- (education major choice, type, and the amount of student loan) and post-borrowing (personal consumption) behaviours and decisions that potentially impact

[1] https://studentaid.gov/understand-aid/types/loans
[2] https://research.collegeboard.org/trends/student-aid/highlights
[3] https://www.forbes.com/advisor/student-loans/average-student-loan-debt-statistics/
[4] https://www.bestcolleges.com/research/student-loan-default-rate-facts-statistics/

their ability to repay the student loans. We also ask the individuals questions that assess their perception of higher education and student loans.[5]

The purely economic factors of the choice of the field of study, measured by the financial compensation offered to graduates at the time of Graduation, significantly impact the respondents' perception of the "worthiness" of student loan borrowing. Given that the universities in the United States charge tuition based on a credit hour and, generally, do not adjust such charges based on the field of study and expected future financial returns from obtaining the degree, the student loan crisis phenomenon may be specifically attributable to the field of study choices made at the outset of the educational journey. We find empirical evidence in support of this hypothesis. Individuals who completed higher education in less financially lucrative fields experience higher loan-to-earnings ratios and exhibit lower levels of satisfaction with their field of study choices and education-related borrowing. Thus, based on our results, a greater focus on discussing financial outcomes in different fields of study may be warranted when the field of study choice is made. A reexamination of the conventional flat rate per credit tuition model presently employed by the universities may also be justified.

Additionally, we document an admitted lack of fiscal responsibility on the part of the student loan borrowers. On average, borrowers exhibit a sharp increase in personal consumption upon Graduation. Such an increase in consumption has an adverse effect on the ability of individuals to repay student loans, thus amplifying the problem. Our results provide some evidence that suggests that a more rational educational choice and better cashflow management upon commencement of post-graduation employment could result in a significantly better financial outcome on an individual level as well as a reduction in the overall burden of student loans on the economy.

2. Literature Review and Hypotheses

Several theories have been used to explain the decision to use student loans to pay educational expenses. The Human Capital theory (Becker, 1993; Becker & Tomes, 1979; Mincer, 1962; Schultz, 1960) suggests that individuals will make a cost-benefit decision and take on student debt if the benefits of making this decision are higher than the costs associated with it. In a literature review on the topic of student loans, Cho, Kiss and Xu (2015) conclude that research supports the view that education is an investment which normally results in an increase in lifetime earnings. This view is also supported by the empirical evidence documented in Timmerman and Volkov (2020). Interestingly, the higher education system does not appear to recognise the cost-benefit analysis that a prospective student goes through, as the per-credit tuition does not generally vary between courses and degrees that may offer vastly different expected earnings.[6]

Generally, the economic benefit of college education has been shown to be held in multiple scenarios. Early on, Morgan and David (1963) concluded that increased investment in education has several economic benefits, among which the most directly observed is the increased earning capacity. In addition to overall higher earnings, more education also translates into steadier and more secure jobs.[7][8] Additionally, Skoog, Ciecka, and Krueger (2019) document a consistent and significant

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[5] Our data was collected prior to the widespread student loan forgiveness programs. Thus, the reported responses are not affected by the ongoing uncertainty as to the need to repay existing loans due to the increased probability of forgiveness of such loans.

[6] The exception to this statement, in some instances, may be medical and law schools.

[7] Based on the College Board newest trend reports for 2020-2021, the average price of higher education continues to go up year over year, from 0.9% for the public four-year out of state institution to 2.1% for a private nonprofit four-year college. The price averages from $3,770 for a two-year institution, to $10,560 and $27,020 respectively for a public four year in and out of state college and to $37, 560 for a private school.

[8] Based on the data provided by the Bureau of Labor and Statistics (www.bls.gov), there is a consistent inverse relation between the level of education and the unemployment rates in the United States. This inverse relation spans back for decades.

increase in the duration of labour force participation for individuals with higher levels of education. For example, a 25-year-old male with a high school diploma is expected to be active in the labour force for 32.6 years; a 25-year-old male with a bachelor's degree is expected to be active for 38.03 years, while a 25-year-old male with a master's degrees is expected to be in the labour force for an additional 38.66 years. This result again speaks to the positive relation between the level of education and the level of lifetime earnings.

Over time, the education-driven pay gap may have somewhat narrowed, and arguments in favour of education shifted slightly, but the central theme remains the same: on average, more education translates into more lifetime earnings. While it is easy to identify outliers who, despite the lack of a higher degree, became financially successful, our goal is to study average individuals and the education and career choices they made. Brown, Fang, and Gomes. (2012) estimated that the average return on a college education over high school is $300,000. However, the degree, the choice of college and the occupation choice add significant variability to this figure.

The benefits of going to college extend beyond just finances. Flint (1997) points out the sociological implications of attaining a college degree in an early paper. Among them are mentioned status attainment in terms of social mobility and social integration. Oreopoulos and Salvanes (2011) link more schooling with a lower probability of being unemployed and with a higher probability of being married, being healthier, having more successful children and being more civically engaged. At the same time, while getting a college degree results in overall positive outcomes, financing the degree with student loans is not as straightforward. Having higher student loans may influence the quality of life and other financial decisions of an individual. This is evident by the present high rates of default on student loans. Brown et al. (2014) document a negative association between higher student loan debt and home purchases, access to credit and ability to pay other debt. Anderson (2013) and Shao (2014), among others, argue that people who have student loans are less likely to be married or have children. Dugan and Kafka (2014) studied individuals who had more than $50,000 in student debt and showed that such individuals were less likely to do well in the areas of finances, well-being, and health. Interestingly, the above studies did not take a deeper look at the fields of study of the borrowers. Such generalised results are useful but may potentially lead to unnecessarily broad conclusions and result in suboptimal policy decisions.

Elliot and Nam (2013) use the Survey of Consumer Finances to find that, in 2009, a household that had student loan debt also had about $40,000 less in assets as compared to a household without student loan debt.[9] Hiltonsmith (2013) calculated the average student loan debt burden of a family to be $53,000, which results in a lifetime asset loss of $208,000, most of it coming from lower retirement accumulations. While these findings may be useful and reliable, they fail to examine the asset levels of similar individuals who made the decision not to take on student loans and, thus, not to obtain higher education. Given the documented positive relation between higher education and lifetime earnings, one would expect that the (long-term) financial worth of individuals who had student loans may be below those who received higher education without taking on student loans. However, such individuals' wealth likely exceeds the wealth of those who did not take on student loans and did not receive higher education. This, of course, is an argument that would support the use of financing for higher education.

Avery and Turner (2012) conclude that the earnings premium increased by more than the college tuition over a long period of time, which means that borrowing for college is not only optimal but also that the cost of it has been dropping in relation to the growth of the long-term earnings that is gained through higher education. Nevertheless, the authors point out that even though borrowing for college might make sense, a debt (risk) adverse student may decide against it, bypassing higher potential

[9] Note that the lower assets level may not be solely driven by the presence of student loans, rather it could also stem from the lower initial wealth level of the household.

earnings. In a theoretical setting, Cigno and Luporini (2019) show that student loans improve job matching and bring educational investment closer to efficiency. Cho, Xu, and Kiss (2015) point out that in order "to solve the life cycle utility maximisation problem, a student is believed to weigh the cost of student loan debt against the probability of college graduation and expected future earnings" (page 234). There are no simple tools to accurately assess both the probability of successful Graduation and the exact future earnings.

The life cycle theory (Modigliani, 1986) predicts that the choice of major should not be affected by the debt a student chooses to undertake, as the debt repayments should represent only a small component of one's earned income over the duration of the repayment period. In other words, taking on student loans and the amount taken should not influence the selection of the major field of study and the type of job chosen. Furthermore, the theory predicts that individual financial decisions should not be affected by the amount of student loans. Empirically, this may not hold.

The reality is that life decisions are affected by the amount of student loans taken. For example, Rothstein and Rouse (2011) devised an experiment in which they have shown that debt is related to choosing higher-paid private jobs rather than lower-paid public jobs. Kuzma, Kuzma and Thiewes (2010) show that the choice of the major drive's students' confidence in how well they can repay their debt. Gicheva (2011) examines the relationship between student loans and the timing of the marriage, concluding that the amount of student loans is negatively related to the decision to marry.

Alternatively, the human capital theory (see Becker, 1993) predicts that the amount of student loans taken is an optimisation problem that is invariably linked to the choice of the major. In the current paper, we explore the alternative theories and the student's perception of student loans post-graduation. Dearden (2019) argues that to design student loan systems, it is imperative to predict students' earnings and income potential in the future. This is important for assessing the burden of any taxpayer costs and the repayment estimated and the hardships associated with it for the individual borrower. Despite the lack of tools and the complexity of the decisions, students make rational choices when it comes to taking on student loans. While universities may not necessarily follow market forces, students (consumers) appear to do so. They appear to be aware of the economic implications of selecting a particular major and the income that comes with it and adjust accordingly. This is evidenced by the recent increased enrollments in STEM-related majors and business schools and the drops in enrollments in the liberal arts fields and other areas of study that presently offer lower economic rewards upon Graduation. In our empirical setting, we explore the idea that people are rational in that the ratio of loans to post-graduation pay is influenced by the choice of the field of study and that the individuals who are studying in the more financially lucrative fields are more likely to take on greater student loan balances.

If the above hypothesis holds that there exists a relation between the future expected earnings and the amount of the student loans, this could imply that the ability to repay the loans stays somewhat consistent across the different areas of study. This finding would further put in question the origin and the causes of the "student loan crisis". One of the less studied potential explanations of the origin of the student loan crisis is the consumption behaviour or the changes in the consumption behaviour of individuals upon securing post-graduation earnings (gaining post-graduation employment in the labour market). We argue that the disproportional consumption to income changes that do not account for the need to repay student loans may be a major driver of the present student loan problem. Johnson and Li (2007) studied the link between higher household debt and consumption smoothing. They find evidence that a high household debt service ratio does not mean a higher sensitivity of consumption to changes in income. Thus, it is possible that individuals who have high student loans over-adjust their consumption upward upon securing post-graduation employment. Such overadjustment would then result in diminished ability to repay student loans. We study how the perceptions about student loans are influenced by the loan-to-pay ratio and by the personal consumption adjustment after Graduation.

The lifecycle theory predicts that the accumulation of student loans should have little (if any) effect on consumption. Because the income is seen as permanent, individuals with student loans should not behave any differently than those who do not take on loans. This, however, could reduce their ability to pay on the loans and thus may be one of the major causes of the high delinquency and default rates on the loans. Flint (1997) identifies lower disposable income as one of the main factors leading to loan default.

If one subscribes to the lifecycle theory, then we would not expect a relationship between consumption and income to student loan balance ratios after Graduation. On the one hand, if there is a regard for one's post-graduation overall financial position and the need to repay student loans, we would not expect to see an upward adjustment in consumption upon Graduation. On the other hand, graduates could be rational, and their consumption behaviour after Graduation would coincide with their debt/income obligations. Borrowers may not sufficiently consider their debt obligations when making consumption decisions; they may end up with a consumption increase that hinders their ability to repay loans, and this, in turn, can influence their perception of the usefulness of the education they obtained and student loans as an instrument to finance the education. Our second goal is to examine the impact of the loan-to-pay ratio on the perceptions of students toward higher education and student loans after Graduation. We argue that higher satisfaction with and the major of study selection and positive perception toward student loans is related to the loans-to-pay ratio post-graduation.

3. Data Analysis and Results

Using social media distribution channels, we conducted a survey of recent higher education graduates during the spring of 2020.[10] We collected 587 responses, with 65 respondents, or 11.07%, enrolled at a higher education institution at the time of the survey. The rest of the respondents, 88.93%, had either graduated or dropped out of a higher education program prior to responding to the survey. Specifically, 4.26% of the respondents attended higher education institutions but have not graduated/dropped out, 4.60% have attained an associate degree, 34.07% secured a bachelor's degree, while 37.48% had a master's degree, and 19.59% had a terminal degree. The distribution of the sample may not be representative of the education levels of the overall population of the United States. We were intentionally targeting participants who completed bachelor's and advanced degrees and thus can self-assess the worthiness of their education and the contribution of student loans as a mechanism of obtaining higher education.

The survey included 36 questions, split into categories on demographics, education, student loans, earnings, changes in personal consumption, self-assessment of the worthiness of education, and self-assessment of the worthiness of student loans.

First, we present univariate results. One of the main objectives of our study is to understand self-perceived attitudes towards student loans as related to majors of studies, universities attended, and income post-graduation. Thus, there is great value in looking at univariate data. However, we proceed to multivariate analysis, specifically OLS regression, to make any conclusions and implications. The data is checked for distribution (normally distributed) and heteroskedasticity. As the dependent variables are a series of categories (4 or 5), we first recode the data to create new variables to make meaningful comparisons. We check the coefficients between variables (correlation coefficients and VIFs within normal range) and the correlations between the independent variables and the error terms in the regression model for endogeneity.

[10] The survey was conducted prior to the discussion and implementation of the student loan forgiveness programs implemented by the Biden Administration in 2022.

3.1 General Data Overview

Table 1A presents the distribution of the student loan balances by the education level of the survey respondents. Some notable observations from Table 1A are that 33% of the participants who dropped out did not take on any student loans. The same is true of Professional or PhD degrees. By comparison, 13% of the respondents who dropped out accumulated between $40k-$50k in student loans, while 46% of respondents with terminal or PhD degrees accumulated more than $100k in student loans. Some key takeaways from this data distribution are that 20% do not borrow anything to go to college or obtain higher degrees. Of particular concern is that 67% of the respondents who dropped out took out between $5k and 50k in student loans; most students who obtain an Associate's, a bachelor's or a master's degree borrow between $10-40k; and almost 50% of those who have a terminal or professional degree take on more than $100k in loans (this result is driven by majors such as law and medicine).

Table 1 Panel A: Student Loans and Degree Completion
Panel B: Student Loans and the Types of Loans
Panel C: Student Loans and the Type of College Attended

Panel A Total Student Loans at Graduation

Highest Education	$0	<$5,000	$5,000-$10,000	$10,001-$20,000	$20,001-$30,000	$30,001-$40,000	$40,001-$50,000	$50,001-$60,000	$60,001-$70,000	$70,001-$80,000	$80,001-$90,000	$90,001-$100,000	>$100,001	Overall
Dropped out	33%	0%	21%	13%	8%	8%	13%	0%	0%	0%	0%	4%	0%	4.44%
Associate's	35%	0%	4%	15%	12%	4%	8%	12%	0%	4%	4%	4%	0%	4.81%
Bachelor's	23%	5%	7%	14%	18%	9%	9%	3%	5%	2%	2%	1%	3%	35.12%
Master's	17%	1%	5%	10%	10%	11%	7%	12%	4%	6%	3%	6%	8%	40.11%
Professional and PhD.	12%	0%	1%	2%	5%	2%	4%	4%	6%	4%	6%	8%	46%	15.53%
Overall	20%	2%	6%	11%	12%	9%	8%	7%	4%	4%	3%	4%	11%	-

Panel B Total by Type of Loan

Loan Type	<$5,000	$5,000-$10,000	$10,001-$20,000	$20,001-$30,000	$30,001-$40,000	$40,001-$50,000	$50,001-$60,000	$60,001-$70,000	$70,001-$80,000	$80,001-$90,000	$90,001-$100,000	>$100,001	Overall
Federal Subsidized	4%	20%	38%	16%	4%	12%	2%	0%	2%	0%	0%	2%	11.63%
Federal Unsubsidized	9%	21%	15%	18%	12%	0%	9%	9%	0%	0%	0%	6%	7.67%
Combination of S and U	2%	5%	13%	17%	13%	8%	8%	5%	6%	2%	7%	13%	50%
Private	17%	25%	0%	33%	0%	8%	8%	0%	0%	8%	0%	0%	2.79%
Combination and F and P	0%	2%	3%	9%	10%	13%	12%	8%	5%	7%	8%	25%	27.91%
Overall	3%	7%	13%	15%	10%	9%	9%	5%	5%	3%	6%	14%	-

Panel C Total by School Type

School Type	$0	<$5,000	$5,000-$10,000	$10,001-$20,000	$20,001-$30,000	$30,001-$40,000	$40,001-$50,000	$50,001-$60,000	$60,001-$70,000	$70,001-$80,000	$80,001-$90,000	$90,001-$100,000	>$100,0001	Overall
In state public	23%	3%	7%	12%	13%	10%	8%	7%	3%	3%	3%	3%	5%	53.83%
Out-of-state public	13%	0%	3%	5%	13%	5%	5%	5%	10%	7%	2%	7%	25%	11.21%
Private	18%	1%	3%	11%	12%	7%	7%	8%	5%	4%	2%	5%	18%	34.95%
Overall	20%	2%	5%	11%	12%	8%	7%	7%	4%	4%	3%	4%	12%	-

Table 1B breaks down the information by the type of student loan obtained. Respondents self-report the student loans by the federal subsidised, federal unsubsidised, a combination of the two types of federal loans, private loans, and a combination of private and federal loans. We find that most loans are issued through federal programs, and the need to use private loans in addition to federal loans drives the higher outstanding balance of respondents. This makes logical sense for high loan balances (for example, paying for law school), but it does not for respondents with relatively low loan balances upon Graduation. Finally, in Table 1C, we link the amount of student loans taken with the type of school attended. The most balanced are accumulated by respondents who choose to attend an out-of-state public school and pay the out-of-state tuition. Those balances exceed the ones reported by respondents who attended private schools. This result is interesting and somewhat alerting in that the decision to attend a public institution out of state may contribute to the lower ability to repay student loans.

In order to understand the decision to finance education through student loans, we also collect and report the data by graduating/current GPA and by the field of study. Tables 2A, 2B, and 2C present this information. As expected, individuals with higher GPAs are less likely to borrow. We speculate that the decision is driven by a higher probability of obtaining financial assistance in the form of scholarships and grants. Nevertheless, when it comes to very large borrowed amounts of over $100K, the amount does not seem to be an artefact of the GPA, with graduates who have a 2.5-3.0 GPA being as likely to accumulate $100k in student loans as respondents with a 3.5-4.0 GPA.

Table 2 Panel A: Student Loans and GPA
Panel B: Student Loans and Degree
Panel C: Student Loans and Starting Pay

Panel A	**Total Student Loans at GPA**													
GPA	$0	<$5,000	$5,000-$10,000	$10,001-$20,000	$20,001-$30,000	$30,001-$40,000	$40,001-$50,000	$50,001-$60,000	$60,001-$70,000	$70,001-$80,000	$80,001-$90,000	$90,001-$100,000	>$100,0001	Overall
2.01- 2.5 GPA	33%	0%	0%	17%	33%	17%	0%	0%	0%	0%	0%	0%	0%	1.23%
2.51- 3.0 GPA	18%	5%	0%	8%	13%	13%	8%	8%	3%	5%	5%	5%	13%	8.20%
3.01- 3.5 GPA	11%	5%	5%	11%	15%	4%	12%	6%	6%	4%	5%	4%	13%	25.41%
3.51- 4.0%	23%	1%	6%	10%	12%	10%	5%	7%	5%	3%	2%	4%	12%	65.16%
Overall	19%	2%	5%	10%	13%	9%	7%	7%	5%	4%	3%	4%	12%	-

Panel B	**Total Student Loans by Field of Study**													
Field of Study	$0	<$5,000	$5,000-$10,000	$10,001-$20,000	$20,001-$30,000	$30,001-$40,000	$40,001-$50,000	$50,001-$60,000	$60,001-$70,000	$70,001-$80,000	$80,001-$90,000	$90,001-$100,000	>$100,001	Overall
Agricultural and life sciences	29%	6%	12%	12%	18%	6%	12%	6%	0%	0%	0%	0%	0%	3.43%
Art's	30%	4%	4%	13%	13%	4%	4%	0%	0%	4%	0%	9%	13%	4.65%
Business	26%	2%	4%	10%	15%	8%	5%	9%	6%	4%	2%	5%	3%	34.34%
Engineering	31%	0%	13%	13%	6%	0%	19%	6%	6%	0%	0%	0%	6%	3.23%
Education	18%	1%	7%	13%	14%	13%	13%	6%	2%	2%	1%	2%	5%	16.77%
Health Science and Public Health	13%	0%	4%	4%	4%	13%	2%	4%	9%	4%	9%	9%	24%	9.29%
Humanities	10%	7%	14%	10%	10%	0%	0%	7%	7%	10%	0%	14%	10%	5.86%
Journalism and Communication	6%	13%	13%	13%	6%	13%	6%	6%	13%	0%	6%	0%	6%	3.23%
Medical / Dental / Pharmacy / Veterinary	9%	0%	13%	16%	13%	3%	3%	6%	0%	0%	6%	0%	31%	6.46%
Law	6%	0%	0%	9%	6%	6%	9%	3%	3%	3%	6%	3%	47%	6.87%
Liberal Arts	24%	0%	0%	7%	7%	7%	10%	17%	3%	14%	0%	3%	7%	5.86%
Overall	20%	2%	6%	11%	12%	8%	7%	7%	5%	4%	3%	5%	11%	-

Panel C	**Total Student Loans by Starting Pay**													
Starting Pay	$0	<$5,000	$5,000-$10,000	$10,001-$20,000	$20,001-$30,000	$30,001-$40,000	$40,001-$50,000	$50,001-$60,000	$60,001-$70,000	$70,001-$80,000	$80,001-$90,000	$90,001-$100,000	>$100,001	Overall
$10,001-$20,000	26%	4%	7%	11%	11%	13%	9%	2%	7%	7%	0%	0%	4%	9.18%
$20,001-$30,000	17%	4%	15%	13%	15%	7%	7%	3%	0%	4%	7%	4%	3%	14.17%
$30,001-$40,000	17%	4%	5%	14%	11%	9%	12%	8%	4%	4%	2%	3%	7%	23.75%
$40,001-$50,000	16%	0%	5%	8%	16%	12%	4%	8%	5%	4%	1%	4%	18%	15.37%
$50,001-$60,000	24%	0%	1%	15%	10%	9%	7%	4%	4%	1%	4%	6%	13%	13.57%
$60,001-$70,000	9%	0%	3%	6%	6%	9%	6%	9%	12%	9%	6%	15%	12%	6.79%
$70,001-$80,000	8%	0%	0%	8%	15%	4%	4%	15%	8%	4%	4%	8%	23%	5.19%
$80,001-$90,000-	30%	0%	0%	0%	10%	10%	0%	20%	0%	0%	0%	10%	20%	2.00%
$90,001-$100,000	31%	0%	8%	8%	8%	0%	8%	8%	0%	8%	0%	0%	23%	2.59%
$100,001-$125,000	25%	0%	6%	0%	19%	13%	0%	13%	6%	0%	0%	6%	13%	3.19%
$125,001-$150,000	22%	0%	0%	0%	22%	11%	0%	22%	11%	0%	0%	0%	11%	1.80%
>$150,001	25%	0%	0%	0%	8%	0%	8%	0%	0%	0%	0%	8%	50%	2.40%
Overall	19%	2%	6%	10%	12%	9%	7%	7%	5%	4%	3%	5%	12%	-

Panel B breaks down the loans by the field of study. Our sample consists of 34.34% of respondents with degrees in a business-related major, 16.77% in education, 9.29% in public health and science, 6.87% in law, 6.46% in medical/dental pharmacy/veterinarian field, 5.86% in liberal arts and humanities. The rest of the sample, with less than 5%, consists of responses from individuals with degrees in agricultural sciences, arts, engineering, and journalism/communications. Consistent with rational choice theory, respondents in high-paying fields have higher amounts of student loans. Based on the entry-level salaries and expected lifetime earnings, we would expect a medical student to have more student loans than a humanities student. The first look at the data by profession points to signs that students in certain majors, like education and liberal arts, appear to be overleveraged. This is further explored in the multivariate analysis that follows the present section.

Next, in Panel C, we present the analysis using the sorting of the data by the amount of student loans and the post-graduation earnings. Of special interest are the numbers highlighted in green (where the ratio of student loans to starting pay is low) and red (where the ratio of student loans to starting pay is higher than one). As we have previously pointed out, looking at the student loan "problem" on a global scale may result in misleading findings. In the present study, we attempt to address the problem by looking at more specific scenarios (combinations of education choices and level of acceptable borrowing) of when it is economically feasible to finance a specific degree with an appropriate level of student loans. As such, it is of concern when, for example, 15% of respondents report a starting pay of $60-70k and student loans of $90-100k. By comparison, someone whose starting pay is $150k+ and who has the same student loans of $90-100k at Graduation is likely to be able to enjoy a higher standard of living while effectively paying on their student loans in the years following Graduation.

The next part of the survey focused on the respondents' self-perception regarding the student loans taken. Table 3 presents the data by major and a scale of agreement that ranges from strongly agree to strongly disagree when answering the question of whether the selected major improved the respondent's standard of living and whether the student loans accumulated during the degree acquisition were worth it to the respondent.

The summary of the responses provided in Panel A suggests that the highest dissatisfaction with the major selection is experienced in the fields of Arts, Journalism and Communication, and Liberal Arts, while the highest level of satisfaction is observed in Business, Engineering, Medical and Legal fields. The most neutral responses appear in the areas of Agricultural and Life Science and Humanities.

Table 3 Panel A: Student Loans and Standard of Living
Panel B: Worthiness of Loans
Panel C: Satisfaction with the Major Selection

Panel A — Did Major Selection Improved Financial Standard of Living?

Agree/ Disagree	Agricultural and life sciences	Arts	Business	Engineering	Education	Health Science and Public Health	Humanities	Journalism and Communication	Medical/Dental/ Pharmacy/Veterinary	Law	Liberal Arts	Overall
Strongly Agree	7%	10%	53%	63%	21%	25%	4%	13%	52%	53%	11%	34.59%
Somewhat Agree	40%	20%	29%	13%	44%	36%	33%	25%	31%	28%	27%	31.87%
Neither Agree nor Disagree	33%	20%	10%	6%	14%	23%	26%	13%	0%	9%	24%	14.26%
Somewhat Disagree	7%	15%	6%	6%	15%	2%	22%	19%	7%	3%	16%	9.43%
Strongly Disagree	13%	35%	2%	13%	6%	14%	15%	31%	10%	6%	22%	9.85%

Panel B — Loans Were Worth It?

Agree/ Disagree	Agricultural and life sciences	Arts	Business	Engineering	Education	Health Science and Public Health	Humanities	Journalism and Communication	Medical/Dental/ Pharmacy/Veterinary	Law	Liberal Arts	Overall
Strongly Agree	20%	5%	35%	44%	16%	12%	25%	13%	32%	24%	11%	24.11%
Somewhat Agree	20%	15%	23%	6%	33%	23%	11%	25%	35%	41%	17%	24.53%
Neither Agree nor Disagree	33%	30%	25%	25%	21%	28%	18%	13%	6%	6%	23%	21.38%
Somewhat Disagree	13%	20%	12%	19%	15%	23%	25%	13%	10%	12%	20%	15.30%
Strongly Disagree	13%	30%	6%	6%	15%	14%	21%	38%	16%	18%	29%	14.68%

Panel C — Happy with Higher Education and Major

Agree/ Disagree	Agricultural and life sciences	Arts	Business	Engineering	Education	Health Science and Public Health	Humanities	Journalism and Communication	Medical/Dental/ Pharmacy/Veterinary	Law	Liberal Arts	Overall
Happy	40%	50%	81%	81%	69%	57%	61%	38%	79%	81%	49%	68.76%
Happy but Wrong Major	47%	40%	13%	13%	22%	34%	29%	44%	14%	13%	38%	22.64%
Not Happy	13%	10%	6%	6%	9%	9%	11%	19%	7%	6%	14%	8.60%

The main takeaways from the data are reported in Table 3. Panel B shows that students majoring in business, engineering, education, medicine, and law overall think that it is worthwhile to take on student loans to obtain their degrees. Students majoring in arts, humanities, journalism, and liberal arts overall think that the accumulated student loans were not worth the while. For example, 49% of the respondents with degrees in liberal arts disagree or strongly disagree that the loans were worth it. By comparison, 58% of business graduates agree or strongly agree that the loans were worth it. To further understand if the answer was driven by the student loan amount or the selection of the major, in Panel B, we ask the participants to reflect on how happy they are with the major chosen in college.

The results are consistent with the responses to the previous question, pointing out that the choice of the major cannot be separated from the pay upon Graduation and the decision to finance college education through student loans. Again, business, engineering, education, medical and law graduates are overall satisfied with their choice of profession, while agriculture, arts, humanities, journalism, and liberal arts graduates are not. For example, 81% of law school graduates are happy with their choice of major, while only 38% of journalism majors are. Interestingly, over 90 percent of the sample are satisfied with their decision to obtain higher education. This confirms that higher education is perceived as a value-adding proposition.

3.2 Consumption Data Overview

As noted in the introductory section of this paper, the personal consumption behaviour of graduates, and more specifically, the (over) adjustment of personal consumption of individuals upon Graduation, may be a cause of the present state where a large amount of student loans are in or at risk of default. To further contribute to the literature on the topic, we explore the changes in the personal consumption behaviour of our survey respondents.

This part of the study focuses on exploring how individuals see their own consumption, how fast and to what degree they adjust their consumption to the higher post-graduation income level and what impact they perceive such adjustment to have on their ability to repay student loans. Table 4 presents the distribution of responses to certain questions posed in the survey. Panels A and B present the responses by the amount of the student loans outstanding and by the area of study, respectively.

Table 4 Panel A: Perceptions of Spending and Student Loans
Panel B: Perceptions of Spending and Major
Panel C: Follow-Up

Panel A	**Spent too much on car, house, going out, vacations upon Graduation?**													
Total Borrowed	$0	<$5,000	$5,000-$10,000	$10,001-$20,000	$20,001-$30,000	$30,001-$40,000	$40,001-$50,000	$50,001-$60,000	$60,001-$70,000	$70,001-$80,000	$80,001-$90,000	$90,001-$100,000	>$100,0001	Overall
Yes	31%	36%	44%	44%	49%	46%	41%	51%	38%	38%	44%	54%	45%	42.52%
No	69%	64%	56%	56%	51%	54%	59%	49%	63%	62%	56%	46%	55%	57.48%

Panel B	**Spent too much on car, house, going out, vacations upon Graduation?**											
Field of Study	Agricultural and life sciences	Arts	Business	Engineering	Education	Health Science and Public Health	Humanities	Journalism and Communication	Medical/Dental/ Pharmacy /Veterinary	Law	Liberal Arts	Overall
Yes	47%	52%	39%	69%	51%	57%	31%	50%	38%	47%	50%	45.54%
No	53%	48%	61%	31%	49%	43%	69%	50%	63%	53%	50%	54.46%

Panel C	**Happy with Higher Education and Major**											
Agree/ Disagree	Agricultural and life sciences	Arts	Business	Engineering	Education	Health Science and Public Health	Humanities	Journalism and Communication	Medical/Dental/ Pharmacy/Veterinary	Law	Liberal Arts	Overall
Strongly Agree	0%	12%	12%	15%	10%	17%	15%	21%	13%	26%	18%	13.53%
Somewhat Agree	17%	35%	17%	21%	23%	24%	8%	29%	35%	22%	6%	20.30%
Neither Agree nor Disagree	33%	53%	44%	46%	31%	12%	46%	21%	26%	26%	29%	34.09%
Somewhat Disagree	25%	0%	14%	8%	18%	24%	15%	14%	13%	13%	24%	16.04%
Strongly Disagree	25%	0%	14%	8%	18%	24%	15%	14%	13%	13%	24%	16.04%

Overall, 42.5% of respondents identify having spent too much on consumption (in terms of spending too much on a new car, house, going out, and going on vacations) after Graduation. Notably, the proportion of those who think that they overspent grows as the borrowed amount increases. This result points to the fact that individuals appear to recognise that their personal consumption actions affect their ability to repay student loans. However, this is an ex-post response, and thus, it suggests that the over-adjustment in consumption may contribute to the student loan crisis.

When the field of study dimension is examined, 69% of engineering and 57% of health science and public health graduates identify themselves as having spent too much, while 61% of business, 69% of humanities, and 63% of medical students do not believe they have overspent upon Graduation. Generally, we see the following trends: individuals who borrow little or do not borrow at all seem to be more fiscally conservative, while almost half of the sample identify themselves as overspenders. As a follow-up question (see Table 4C), we asked the respondents to evaluate whether they believe they should have paid more toward student loans than they did/presently do. We see a relatively even distribution of opinions on the topic of paying/not paying off the loans faster. Journalism and communication, medical, and law graduates appear to underpay on their loans upon Graduation (underpay refers to their perception as to how much they should have paid as opposed to actual loans being underpaid on). The implication we draw from the answers is that unless the money that would otherwise be used to pay off the student loans is invested in higher return assets, prior payments for educational expenses (i.e. student loans) should be considered as a sunk cost (the asset that was obtained using this money does not appreciate).[11] Thus, one should put effort into paying such loans off as soon as possible to reduce the burden on future cash flows. This may (should) be achieved through a more fiscally responsible management of personal consumption upon Graduation.

3.3 Multivariate Analysis

To further investigate the relations between student loans, employment-related outcomes, and perceptions of borrowers toward higher education and student loans, we perform multivariate analysis. First, we focus on the relationship between financial satisfaction with the chosen major and the loan-to-pay ratio. The results of the tests are presented in Table 5. We asked borrowers/former students to assess their own perceptions of whether their college major increased their standard of living post-graduation. The dependent variable is represented by the degree of agreement with the statement that the chosen major increased/will increase the standard of living after Graduation; the main independent variable is the loans to starting pay ratio. For robustness checks, we also include alternative measures for the dependent variable. Specifically, we use the log of student loans instead of the ratio and the student loans to median pay in the industry. These alternative measures address the issue of self-selection bias (only students who have little in loans and a high salary decide to answer the survey) and representativeness. Our results are consistent with the main findings and are available on request.

Several control variables, such as gender and GPA, are included in the models based on prior findings. Yankovich et al. (2019) find that gender significantly impacts student loan borrowing and the perceived impact of debt on academic performance. Additionally, we include the consumption adjustment variable as it relates to the satisfaction with the choice of the major. After presenting the overall data (Model 1), we split the sample into two subsamples (results reported in Models 2 and 3) based on the labour force demand/marketability and starting pay in the respective groups of major fields of study. As such, category one (Model 2) is comprised of students who majored in arts, humanities, journalism, liberal arts, agriculture/life sciences and education-related majors. The second category (Model 3) consists of responses from business, engineering, health-related degrees, law and medicine majors.

[11] This is in contrast to, for example, having a mortgage on a home.

Table 5

Variable	Model 1	Model 2	Model 3
Loans/Pay	-.0991 (0.072)*	-.2595 (0.000)***	-.0637 (0.211)
DegreeCategory	.8979 (0.000)***		
GPA	.0932 (0.552)	.1700 (0.587)	.0327 (0.843)
Gender	.3175 (0.011)**	-.0976 (0.713)	.4620 (0.001)***
ConsumptionScore	.0696 (0.006)***	.0530 (0.211)	.0736 (0.013)**
Constant (p-value)	2.753 (0.000)***	2.7461 (0.020)**	3.7609 (0.000)***
F model (p-value)	22.17 (0.000)***	5.12 (0.0006)***	4.74 (0.0010)***
R-squared	0.1945	0.0771	0.0818
Fixed Effects	Yes	No	No
N	449	192	257

Note: The dependent variable is coded as a scale from 1 to 5, representing the degree of agreement with the statement: "I feel like the major I chose has increased/will increase my financial standard of living after graduation". It is represented by a scale from 1-5, where 1 is strongly disagree and 5 is strongly agree. Independent variables are as follows: Loans/Pay is the log of the midrange of loans at current time/Graduation to starting pay, DegreeCategory is a dummy variable equal to 1 if the respondent was a business, engineering, health administration, law or medicine major and 0 otherwise, GPA midrange and gender (equals 1 if the respondent identifies as male and 0 otherwise), ConsumptionScore is the calculated number based on answers to four different questions about increases in the individual's standard of living after Graduation. Model 1 presents the overall data. It includes major fixed effects, and Models 2 and 3 present the data by category, where Model 2 is comprised of students who majored in arts, humanities, journalism or liberal arts, agriculture/life sciences and education and Model 3 of former students in business, engineering, health, law, and medicine.

Model 1 (the combined model) shows that there is an inverse relationship between financial satisfaction with one's major choice and the loan-to-pay ratio, an expected result that implies that the satisfaction is reduced when the loan balance (as percent of pay) is greater. The positive relationship between satisfaction with the major selection and consumption upon Graduation leads us to infer that the way borrowers perceive their chosen major is directly related to the amount of money they have available after Graduation and to the improvement in the standard of living. The relationship between the money-making ability that the selection of the major provides and the satisfaction with the selection is further emphasised by the positive relationship between the level of satisfaction and the educational major category (proxied by the DegreeCategory variable). Majors that are more marketable, i.e. have a high potential to produce greater income, lead to higher financial satisfaction with the major selection decision. This finding supports the idea that students should analyse the post-graduation job market when deciding on both what majors to choose and how much student loans to incur during their educational journey. We also used the individual consumption adjustment answer rather than the aggregate score for robustness checks. The results were similar and consistent with the overall model.

It is possible that the above results of an inverse relation between the student loan-to-pay ratio and the level of satisfaction stem from individuals over-adjusting their personal consumption upon Graduation, which results in a diminished ability to repay student loans. This may lead to a perception that the initial choice of the field of study was not the correct one.

When we break the sample up by subcategories based on the labour market demand and expected earnings (DegreeCategory variable), the relation between the satisfaction from the major selection and the loan-to-pay ratio emphasised for both, the high (Model 3) and low (Model 2) expected earnings major graduates, however, the negative relationship is only highly statistically significant for the lower earnings group (Model 2). The group in Model 3 is comprised of students who majored in business, engineering, health-related fields, law, and medicine – the majors that generally result in higher expected earnings. While present, the negative relationship between the loans-to-pay ratio and satisfaction in this educational category is not statistically significant. This may be explained by the fact that graduates in this educational group may experience similar starting pay to those included in Model 2; however, their expected earnings growth rate may be significantly higher, which in turn results in less fear of higher loan-to-pay ratios. A medical student, for example, can make the determination that, even though she is incurring a large amount of student loans, ultimately, her pay and potential for a job will be sufficient to justify such an expense. We find that, while the negative relationship between financial satisfaction and loans/pay ratio is present, so is a positive relationship between increased levels of consumption and satisfaction (in the overall sample reported in Model 1). In Model 2, which reports the results for former students who majored in arts, humanities, journalism, liberal arts, agriculture/life sciences and education-related majors, we find the relation to hold for the loans to pay ratio, but not the consumption score. In other words, the former students from this category are less likely to be satisfied with the financial outcomes of their major selection when they have greater loan-to-pay ratios and this effect is not offset by the increased satisfaction from the ability to increase personal consumption upon Graduation. This result may indicate that the educational choice of students in this category does not sufficiently contribute to a higher standard of living upon Graduation. Overall, we conclude that a higher loan/pay ratio post-graduation leads to lower financial satisfaction with the chosen major regardless of the major. Individuals who have high student loans compared to their starting pay are more likely to regret their choice of major regardless of what that major was. The consumption adjustment relationship is not as clear. In order to try to understand it better, we focus on the degree to which consumption increases post-graduation.

To further test the application of rational choice theory when it comes to education and career choices, we look at the relationship between the consumption score and the loan-to-pay ratio. The results are reported in Table 6. We build the dependent variable, ConsumptionScore, by combining the self-perceived increase in spending along four variables: increase in expense for transportation (buying a new/better car after Graduation), increases in the living conditions (renting a better/more expensive place), increases in vacation spending, and increases in entertainment spending. We build the aggregate score based on the answers provided by the respondents. Someone who did not increase/adjust their spending in any of the categories is assigned a score of 0, while someone who reported an increase in all four spending categories is given a score of 4.

Table 6

Variable	Model 1	Model 2	Model 3
Loans/Pay	-.1653 (0.059)*	-.2937 (0.042)**	-.1288 (0.169)
DegreeCategory	.6005 (0.007)***		
GPA	-.5940 (0.078)*	-.9587 (0.100)	-.3848 (0.365)
Gender	-.4760 (0.090)*	-.8173 (0.142)	-.3477 (0.284)
Constant (p-value)	5.1007 (0.000)***	6.5800 (0.002_***	4.888 (0.001)***
F model (p-value)	4.06 (0.0030)**	3.00 (0.0316)**	1.14 (0.3331)
R-squared	0.0366	0.0429	0.0172
N	458	198	260
Variable	Model 1	Model 2	Model 3
Loans/Pay	-.1653 (0.059)*	-.2937 (0.042)**	-.1288 (0.169)

Note: The dependent variable is the consumption score, which ranges from 0 to 4, based on each of the categories of increased consumption post-graduation. Independent variables are as follows: Loans/Pay is the log of the amount of borrowed midrange amount from the highest degree and log of the midrange of starting pay, DegreeCategory is a dummy variable equal to 1 if the respondent was a business, engineering, health administration, law or medicine major and 0 otherwise, GPAmidrange and Gender (equals 1 if the respondent identifies as male and 0 otherwise). Model 1 presents the results for the overall sample. It includes major fixed effects. Models 2 and 3, present the data by category, where Model 2 is comprised of students who majored in arts, humanities, journalism or liberal arts, agriculture/life sciences and education and Model 3 former students in business, engineering, health, law and medicine.

We find a negative association between the loans-to-pay ratio and consumption after Graduation, a relation that persists in the overall sample and the lower starting pay degree category subsample (the relation is negative but statistically insignificant in the higher earnings educational group included in Model 3). The higher the loans/pay ratio at Graduation, the lower the increase in consumption. Three possible explanations for these relationships are: (1) reduced levels of disposable income due to student loan payments, (2) an elevated degree of caution in the expenditure decisions that are associated with the higher level of debt, and (3) inability of the individuals to access credit in order to increase their consumption/expenditure. On the one hand, individuals who have a high loan-to-pay ratio may not be willing to increase their standard of living after Graduation because of the impact of student loan payments on their disposable income. Interestingly, the relation described above is only statistically significant for the low-pay major categories (Model 2) but is not significant for the higher expected earnings majors (Model 3).

Regardless of whether the individual is in a high expected earnings major, like medicine, or on the opposite end of the scale, the concern for post-graduation loan payoff may be driving the restricted consumption behaviour. It is also possible that, even if the individuals wanted to increase their standard of living by getting a new car or going on a vacation, they may not be able to do so. Further work is needed to disentangle the effect. However, there is a relation between the post-graduation standard of living and the amount of loans one graduates with. This relation has an impact on post-graduation perception toward the major selection and individual's personal consumption. These findings should be taken into consideration when a decision to take on loans to finance higher education is made.

To further understand the relationship between financial satisfaction in the choice of major, post-graduation student loans to pay ratio and adjustment in consumption, we look at how an increase in the standard of living is related to the satisfaction in major choice. Overall, the test of perception of the major selection on consumption points to an increase in satisfaction when consumption increased only when the individual was able to afford that increase. Overall, there is a strong positive relationship between the perception that a major is responsible for the increased standard of living and the adjustment in personal consumption. The higher the adjustment in consumption, the higher the perception that the major was a positive choice in life that led to a higher standard of living. This result is consistent with the expected rational behaviour.

4. Implications, Limitations and Conclusion

Overall, we find indication that individuals are mostly exhibiting rational decision-making when it comes to career and education choices and to the decision to finance education with student loans. They generally appear to decide on student loans while considering prospective future earnings. This is consistent with rational expectations and human capital theory. We also find that there is a strong association between the perception that a major was worth obtaining and the marketability and the starting pay that jobs requiring specific degrees generally pay.

Extending the argument, we also conclude that the major selection indirectly impacts personal consumption adjustment post-graduation and, in turn, an increase in consumption is associated with a positive view of the chosen major. We find evidence of rational decision-making when it comes to borrowing, major selection and consumption adjustment regardless of the major chosen. Individuals who have a higher loan-to-pay ratio after Graduation adjust their consumption the least.

A shortcoming of the study and potential area to expand is incorporating financial literacy into the consumption and educational choice framework. Artavannis and Karra (2020), Lusardi et al. (2010), Lusardi and Tufano (2015) and Mahdavi and Horton (2014) link financial literacy to understatement of student loan debt, financial mistakes, and correlation with college majors. Extending the analysis along the financial literacy dimensions could shed light on the ex-ante decision-making process.

It is important to mention that this study focuses on the value of financial education from the perspective of the return on the investment. We acknowledge that there is a broader perspective beyond this paper's scope. This could be exacerbated based on current economic conditions and investor sentiment. Prasad et al. (2022) point out the impact of investor sentiment on various dimensions of economic decision-making. Including investor sentiment in the analysis may impact how valuable some majors are, and as a result, the worth of student loans is in the context of the selection of a major. This topic and the incorporation of investor sentiment need to be explored further.

The benefits of education go beyond the return on investment. In this paper, however, we focus on the narrow view of the benefits associated with monetary investment.

Another consideration that could be examined in future work is the availability of programs associated with public loan forgiveness. We have excluded it from this analysis due to its narrow scope and applicability. Despite the talk in the media, few people qualify for any kind of forgiveness. Additionally, forgiveness only applied to public loans. This is a consideration that could be included in future work, especially given the recent changes (and proposed changes) to the public loan forgiveness and, potentially, a new income-based repayment plan.

Our findings may have significant policy implications. It is unrealistic to expect an equal level of increase in the standard of living and consumption across all majors of study. There is an argument to be made for students being able to adjust to market forces and follow them, even when universities do not. A student who has very bleak job prospects should have both information and counselling on those prospects and, potentially, a way to minimise the amount borrowed. Individuals on the other side of this decision have expressed both regret and the desire to make a more educated and restrictive decision about the amount of loans they undertook based on their future job perspectives and potential pay. Society needs highly trained individuals in all fields of study, including those that are known to provide lower earnings. However, the current non-discriminatory tuition policies that charge the same amount to engineering and liberal arts students may, in part, cause student loan crises and, more generally, contribute to overall societal inequalities.

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APPLIED FINANCE LETTERS

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BANK EFFICIENCY AND GOVERNANCE: EVIDENCE FROM JOINT VENTURE AND FOREIGN COMMERCIAL BANKS IN VIETNAM

ENG-TUCK CHEAH[1], THONG DAO[1], THAO NGOC NGUYEN[1]

1. Nottingham Trent University, United Kingdom

* Corresponding Author: Thao Ngoc Nguyen, Nottingham Business School, Nottingham Trent University, United Kingdom. ✉ thao.nguyen@ntu.ac.uk

Abstract

In this paper, we intend to examine the influence of national governance on the bank efficiency of joint ventures and foreign commercial banks in Vietnam. Joint venture and foreign commercial banks have been instrumental in introducing new financial products to the Vietnamese market (e.g., mortgage services and medium-term certificates of deposit). At the same time, they have also penetrated the retail market through automobile and housing loans and international credit card services. We use the DEA double bootstrap method to develop a bank network function to evaluate bank efficiency. The findings from our random-effects model demonstrate that world governance indicators, as proposed by the World Bank, independently determine the bank efficiency of the joint venture and foreign commercial banks in Vietnam. There are important implications to be highlighted for policymakers and stakeholders of joint venture and foreign commercial banks and other types of banks in the banking industry elsewhere around the world.

Keywords: Efficiency; Banking; Bootstrap; Governance indicators

1. Introduction

We first provide background information on the roles played by joint venture commercial banks (JVCBs) and foreign commercial banks (FBs) in Vietnam, along with the motivation, contributions, and major findings, before discussing the impact of institutional theory on bank efficiency. Through our hypotheses, we also examine and discuss the relationships between national governance indicators and bank efficiency.

1.1 Research Background

Vietnam has recently experienced a surge in JVCBs and FBs' growth. What makes them more efficient than local banks? Domestic banks may possess more informational advantages, while JVCBs and FBs may face fewer domestic credit allocation restrictions. Crucially, JVCBs and FBs continue to boost efficiency and competition in the banking sector (Cull & Peria, 2016). Yet, few studies have focused on the effects of national governance on JVCBs and FBs, although numerous have examined the effects of corporate governance on businesses and financial institutions (Koerniadi, 2013; Andries et al., 2018).

Our main motivation is to investigate the role of institutional theory in bank efficiency. Specifically, we investigate how the different national governance indicators provided by the World Governance

Indicators (WGI)[1] influence JVCBs and FBs' overall efficiency. These indicators include corruption control (CC), government effectiveness (GE), political stability and absence of violence (PS), regulatory quality (RQ), rule of law (RL), and voice and accountability (VA). In addition, we included the Corruption Perceptions Index (CPI)[2] as a comparison to CC. To the best of our knowledge, this is the first study to examine the relationship between FB efficiency and national governance in Vietnam.

Studies on national governance have employed a global dataset, reducing specific country features (Lensink et al., 2008; Barth et al., 2013). Furthermore, compared to domestic banks, JVCBs and FBs' performance is influenced by host markets. In developing countries, JVCBs and FBs frequently outperform domestic banks because of their ownership advantages (Claessens et al., 2001; Havrylchyk & Jurzyk, 2005; Pasiouras & Kosmidou, 2007). A banking sector may function at its best if it operates in a financial system predominantly owned by foreigners and heavily regulated by foreign regulators (Tripe, 2013). Furthermore, domestic banks were weakened after the financial crisis (Manlagñit, 2011). In Vietnam, state-owned commercial banks have the largest market share and the best financial outcomes because of their experience and familiarity with the local market, government support, and long history. However, their dominant role will be steadily replaced by foreign-owned and active private banks is a relatively free market. Indeed, in developed countries, JVCBs and FBs underperform domestic banks because of intense competition and lower earnings (De Young & Nolle, 1996). Greenfield banks (100% foreign-owned banks) are more efficient and less risky than other types of JVCBs and FBs (Wu et al., 2011). Thus, determining how JVCBs and FBs perform under the influence of the current national governance in Vietnam can help identify their responsibilities in emerging markets.

Our contributions are three-fold. First, we consider liquidity and overhead expenses as additional determinants of efficiency, which, to our knowledge, has not been done in many studies. This can make our results more reliable and representative of the Vietnamese context. Second, our study has implications for FB practices in developing countries. JVCBs and FBs should account for the economic situation of the country in which they operate and the different aspects of national governance. Hence, market participants, such as traders, investors, and analysts, should pay particular attention to national governance concerns when accounting for FB efficiency. Third, our findings suggest that policymakers should strengthen their country's institutions at the national level and foster an environment conducive to outsiders entering and conducting business successfully for the healthy growth of foreign investment in the banking sector (via JVCBs and FBs). Regulatory quality is the most important factor that influences bank efficiency. Importantly, our results are of direct interest to policymakers in Vietnam and other emerging countries who are assessing the merits of national governance to enhance FB efficiency.

1.2. Institutional Theory and Bank Efficiency

To our knowledge, few studies explore how institutional mechanisms influence bank efficiency, especially in relation to institutional analyses in sociology (Fligstein & Freeland, 1995; Hall & Soskice, 2001; Campbell, 2007). National institutional factors are important determinants of corporate governance behaviours and practices (Denis & McConnell, 2003; Grosvold & Brammer, 2010). Foreign investors and local partners may differ in their corporate governance practices, including the regulatory and political systems arising from legal traditions, education, and welfare. These mutually reinforcing characteristics are known as institutional systems. They can influence bank efficiency input

[1] These indicators are based on hundreds of variables and reflect the views of thousands of citizens, firm survey respondents, and experts worldwide (Kaufmann et al., 2008). Data are available at https://info.worldbank.org/governance/wgi/

[2] https://www.transparency.org/en/cpi

and output measures, including loans, deposits, and securities (Jackson & Deeg, 2008). Based on an unbalanced panel analysis of 4,050 bank observations in 72 countries from 1999 to 2007, Barth et al. (2013) found that tighter restrictions on bank activities are negatively associated with bank efficiency, while greater capital regulation stringency is marginally and positively associated with bank efficiency. Here, we use the WGI to measure national governance. Note that World Governance Indexes (average) and World Governance Indexes (principal component) are the mean values. The principal components include CC, GE, PS, RQ, RL, and VA. Both the average and principal component indexes are positively and significantly related with bank efficiency scores. Next, we propose hypotheses for each indicator's relationship with JVCBs and FBs' efficiency in Vietnam.

1.3. National Governance and Bank Efficiency

1.3.1. Corruption Control

Corruption control (CC) is the extent to which public power is exercised for private gain. This includes petty and grand forms of corruption. Osei-Tutu (2021) found negative effects of increased corruption on bank efficiency. These effects apply to banks of all sizes and countries with various levels of economic development. However, corruption is not always detrimental to bank costs. Corruption may rather help them overcome the distortions created by ill-functioning institutions resulting in faster decision-making and more efficient resource allocation. Using more than 2,000 commercial banks in 27 European Union (EU) countries, Chortareas et al. (2013) found that bank efficiency scores were positively and significantly related with CC. Kamarudin et al. (2016) examined the efficiency of Islamic and conventional banks in Gulf Cooperation Council countries during 2007–2011. The authors found that CC enhances the revenue efficiency of conventional banks. Based on this discussion, we hypothesise the following:

Hypothesis 1: CC is positively related to the efficiency of JVCBs and FBs in Vietnam.

1.3.2. Government Effectiveness

Government effectiveness (GE) represents the quality of the public and civil services, and their independence from political pressure. It also includes the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. GE can be explained by the organisational environment related to economic development and educational status (Garcia-Sanchez et al., 2013). Chortareas et al. (2013) argued that bank efficiency scores are positively and significantly related with GE. Kamarudin et al. (2016) stated that GE enhances the revenue efficiency of both Islamic and conventional banks.

Hypothesis 2: GE is positively related with the efficiency of JVCBs and FBs in Vietnam.

1.3.3. Political Stability and Absence of Violence

Political stability (PS) represents perceptions of the likelihood of governments being destabilised or overthrown by unconstitutional or violent means, including political violence and terrorism. Chortareas et al. (2013) suggested that bank efficiency scores are positively and significantly related with PS. Kamarudin et al. (2016) found that PS enhances the revenue efficiency of conventional banks.

Hypothesis 3: PS is positively related with the efficiency of JVCBs and FBs in Vietnam.

1.3.4. Regulatory Quality

The literature suggests a positive correlation between bank efficiency and regulatory quality (RQ). Banks tend to be more efficient in the presence of better regulations in a country, including regulations for the whole country/economy and the banking sector. Figueira et al. (2009) found that regulatory quality in Latin American countries affects the efficiency of their banks, while Kamarudin et al. (2016) and Özkan-Günay et al. (2013) reached similar conclusions for Islamic countries and Turkey, respectively. Regulations that improve banks' market discipline and the supervisory role of authorities help enhance bank efficiency in terms of both costs and profits (Pasiouras et al., 2009). Interestingly, the favourable impact of supervision is only observed for independent and experienced supervisory bodies (Barth et al., 2013). Profit and cost efficiencies are also boosted by Basel-related regulations and restrictions designed to ensure the robust and efficient operation of banks (Chortareas et al., 2012; Lozano-Vivas & Pasiouras, 2010). Meanwhile, Chortareas et al. (2012) confirmed the adverse effects of interventionist policies (e.g., monitoring the private sector) on bank efficiency. Importantly, Pasiouras et al. (2009) reported a complex relationship between regulations and efficiency, where strict capital requirements help cost efficiency but hurt profit efficiency, whereas activity restrictions demonstrate the opposite effects. Based on this discussion, we hypothesise that:

Hypothesis 4: RQ is positively related with the efficiency of JVCBs and FBs in Vietnam.

1.3.5. Rule of Law

Rule of law (RL) refers to the fundamental principle that everyone (including the government) is equally subject to the law. This is a universal constraint on the behaviour of individuals and institutions. Countries with better RL are 2.5 times as efficient as other countries (Scully, 1988). Better institutional quality and environments also promote more efficient banks and financial institutions (Barth et al., 2013; Chortareas et al., 2013). Kamarudin et al. (2016) documented the positive impact of RL on the revenue efficiency of both traditional and Islamic banks. Although different from banks, microfinance institutions also enjoy the favourable effects of RL on their financial efficiency, while still suffering from managerial inefficiency (Hussain et al., 2021). Meanwhile, Hasan & Marton (2003) argued that the influence of RL is not straightforward, as it negatively affects profit efficiency but positively affects cost efficiency. Among the various aspects of RL, crime and theft are considered the most problematic for business performance (Roxas et al., 2012). Based on this discussion, we hypothesise that:

Hypothesis 5: RL is positively related with the efficiency of JVCBs and FBs in Vietnam.

1.3.6. Voice and Accountability

Voice and accountability (VA) refer to the influence and freedom citizens can enjoy (e.g., voting rights and freedom of speech) (Chortareas et al., 2012). Higher VA is associated with increased bank efficiency (Barth et al., 2013). A banking system tends to be more efficient if political rights and civil liberties are well protected (Figueira et al., 2009). Kamarudin et al. (2016) observed this effect for both conventional and Islamic banks. Interestingly, VA is highly relevant and beneficial to JVCBs and FBs because independent and unbiased media enhance the transparency/coverage and quality of local information and affairs. Examining many countries, Lensink et al. (2008) discovered that although FBs are less efficient than domestic banks, superior national governance alleviates this disadvantage. Based on this discussion, we hypothesise that:

Hypothesis 6: VA is positively related with the efficiency of JVCBs and FBs in Vietnam.

2. Data and Methodology

This section briefly discusses JVCBs and FBs' actions in Vietnam over the past 30 years. Next, we present the dependent and independent variables, and describe the two-stage bootstrap method.

2.1. Joint Venture Commercial Banks and Foreign Banks in Vietnam

Vietnam is one of Asia's recent economic successes, growing at 7.8% annually in the last decade. Compared to other countries, Vietnamese banks are more influenced by economic conditions and government policies. After Vietnam joined the World Trade Organization in 2007,[3] JVCBs and FBs have increasingly challenged domestic banks with their advanced technology, products, and professional management. FBs can also form partnerships with local banks, who can benefit from FBs' expertise in technology, operation processes, financial products, and other areas (Tran et al., 2015). The number of JVCBs has increased from four to six during 1995–2009, whereas that of FBs increased from five to nine during 2014–2018 (Table 1). Despite being governed by the Communist Party, Vietnam is a democratic country that focuses on political stability and economic prosperity.

Table 1: The number of commercial banks from 1990 to 2020

Type of banks	1990	1995	2000	2005	2009	2014	2018	2020
State-owned commercial banks	4	4	5	5	5	4	7	4
Other commercial banks								
Joint stock banks	0	36	39	37	37	34	28	31
JVCBs	0	4	5	5	6	4	2	2
FBs	0	0	0	0	5	5	9	9
Total	**4**	**44**	**49**	**47**	**53**	**47**	**46**	**46**

Note: Sources: SBV (2009, 2014, 2018, 2020).

2.2. Dependent and Independent Variables

Table 2 lists the descriptive statistics of our dependent and independent variables. The dependent variables were the efficiency scores estimated from the input and output variables. The independent variables are the national governance indicators.

Table 2: Descriptive statistics of efficiency inputs and outputs as well as national governance variables

	Mean	Median	Std. Dev.	Min	Max	Skewness	Kurtosis	5%	25%	75%	95%
Panel A: Efficiency inputs											
Deposits											
Customer	31,226	18,868	29,928	775	111,451	1.2694	0.8382	2,683	9,954	43,948	96,067
Other	4,410	3,204	3,398	0	12,901	0.9650	0.2697	385	1,831	6,708	11,548
Staff	562	337	417	50	1,438	0.6629	-0.8374	60	216	805	1,307
Panel B: Efficiency outputs											
Loans											
Customer	20,164	14,340	15,456	523	64,065	0.9178	0.1958	2,102	8,465	31,129	47,494
Other	15,488	9,469	15,851	878	71,348	1.8945	3.8459	2,667	4,125	22,356	44,527
Securities	6,257	4,682	5,523	3	19,740	0.7729	-0.3443	316	1,548	9,405	16,964
Panel C: National governance variables											
CPI	32.860	33.000	2.4579	29.000	37.000	0.2310	-1.1400	29.0000	31.0000	35.0000	37.0000
CC	-0.4896	-0.4807	0.0733	-0.6073	-0.3527	0.0667	-0.7116	-0.6073	-0.5280	-0.4402	-0.3527
GE	-0.0451	0.0057	0.1474	-0.2699	0.2003	-0.2974	-0.9801	-0.2699	-0.2325	0.0383	0.2003
PS	0.1274	0.1891	0.1190	-0.0734	0.2674	-0.3069	-1.4825	-0.0734	0.0255	0.2336	0.2674
RQ	-0.4487	-0.4538	0.1620	-0.6687	-0.1479	0.3093	-1.0022	-0.6687	-0.5988	-0.3494	-0.1479
RL	-0.2058	-0.1339	0.2506	-0.5516	0.0753	-0.2670	-1.6675	-0.5516	-0.5149	-0.0037	0.0753
VA	-1.4059	-1.4057	0.0388	-1.4765	-1.3589	-0.6218	-0.9584	-1.4765	-1.4201	-1.3734	-1.3589

Note: In Panels A and B, the numbers are in million Vietnamese dongs except for Staff (number of people).

[3] Vietnam has further liberated the banking sector to allow greater presence of FBs. Following Decree 22/2006/ND-CP, five FBs (HSBC, Standard Chartered, ANZ, Shinhan, and Hong Leong) can establish their wholly foreign-owned subsidiary banks in Vietnam.

Our inputs include: (i) staff (number of employees), (ii) purchased funds (deposits from the State Bank of Vietnam and other banks), and (iii) customer/core deposits (corporate and private customers). Our outputs include: (i) customer loans (corporate and private sectors), (ii) other loans, and (iii) securities (investment and trading securities) (Berger and Mester, 1997). Our unique dataset included six JVCBs and FBs in Vietnam from 2011 to 2020. Data were collected from the State Bank of Vietnam and annual reports of individual banks. For all variables, the mean and median in Table 2 differ significantly and are closer to the minimum than to the maximum values. This suggests a non-normal and positively skewed distribution with a wide range of values, as shown by the gap between the minimum and maximum values. Furthermore, from the annual reports, we use five bank characteristics (total assets, return on assets, loans, deposits, and staff expenses relative to assets) as control variables.

Our main independent variables include seven national governance indicators for Vietnam. One is from Transparency International (CPI), while six are from the World Bank (CC, GE, PS, RQ, RL, and VA). These variables reflect various aspects of the macroenvironment. By construction, the CPI ranges from 0 (highly corrupt) to 100 (very clean), while the rest range from -2.5 to 2.5, with a higher value indicating better *governance*. Panel C in Table 2 summarises the *national governance* variables. According to the mean and median, national governance in Vietnam is below average, with a CPI below 50, and most other variables are negative. This may be due to an underdeveloped governance system (Nguyen et al., 2015). The only exception is PS, perhaps due to the single-party system (Nam, 1969), and GE to some extent (with a slightly positive median despite a negative mean).

As shown by the standard deviation and range, some variables are more volatile than others because the development of Vietnam’s national governance over time is not uniform in all areas. JVCBs and FBs should pay close attention to this variation if they are interested in certain aspects of national governance. For example, GE had a median of only 0.0057, standard deviation of 0.1474, and range of 0.4702. Meanwhile, PS had a higher median of 0.1891 but a lower standard deviation (0.119) and range (0.3408). The variables demonstrate varying degrees of stability over time, suggesting that some areas of governance are more consistent and stable than others. Three variables are positively skewed (CPI, CC, and RQ), while the rest are negatively skewed. In other words, corruption and RQ occasionally get much better than usual, while other areas sometimes get much worse than usual. Negative values of excess kurtosis across the board indicate that all the variables are platykurtic. Therefore, national governance variables follow a non-normal distribution.

2.3. Bootstrap Two-stage Procedure

We use Simar & Wilson's (2007) two-stage efficiency analysis method. First, data envelopment analysis (DEA) is employed to estimate the technical efficiency of banks based on the inputs and outputs in the sample using either constant (CRS) or variable returns to scale (VRS). Second, a truncated bootstrapped regression is used to bootstrap the DEA scores. We used Algorithm 2 of Simar & Wilson (2007) because it is corrected for bias, and thus, preferred for proper inference. The second stage incorporates the seven national governance indicators besides the five control variables for bank characteristics (Wijesiri et al., 2015).

Consider the *j*th bank with outputs and inputs Y_{rj} and X_{ij} (all positive), where U_r and V_i are the variable weights determined by solving the following problem (Charnes et al., 1978).

$$\text{Max } \hat{\delta}_0 = \frac{\sum_{r=1}^{s} U_r Y_{r,0}}{\sum_{i=1}^{m} V_i X_{i,0}} \tag{1}$$

$$\text{Subject to: } \frac{\sum_{r=1}^{s} U_r Y_{r,j}}{\sum_{i=1}^{m} V_i X_{i,j}} \leq 1 \text{; j = 1, 2,…, n} \tag{2}$$

$$U_r, V_i \geq 0 \text{; r = 1, 2, …, s; i = 1, 2, …, m}$$

The true efficiency score, $\hat{\delta}_0$, is not observed directly but rather empirically estimated. Simar & Wilson's (2007) procedure provides a confidence interval for efficiency estimates and yields consistent inferences for factors explaining efficiency. To implement the bootstrap procedure for DEA, we assume that the original data are generated by a data-generating process and that we can simulate this process using a new (pseudo) dataset drawn from the original data. We then re-estimate the DEA model using the new data. By repeating this process 2000 times, we can derive an empirical distribution of these bootstrap values (Balcombe et al., 2008; Wijesiri et al., 2015). The efficiency scores, $\hat{\delta}_{i,t}$, of bank i obtained in the first stage are regressed on the explanatory variables in the second stage using the following regression.

$$\hat{\delta}_{i,t} = \alpha + \sum_{j=1}^{J} \beta_j X_{i,t}^{j} + \sum_{m=1}^{M} \beta_m X_{i,t}^{m} + \varepsilon_{i,t} \tag{3}$$

where $\hat{\delta}_{i,t}$ is bank *i*'s technical efficiency in period t, which is measured as CRS, CRS biased corrected (CRS-BC), VRS, and VRS biased corrected (VRS-BC); and $X_{i,t}^{t}s$ are the explanatory variables which are grouped into bank-specific $X_{i,t}^{j}$, and industry specific and governance variables $X_{i,t}^{m}$.

3. Empirical Results

We first present the efficiency scores, followed by the regression results and implications. Finally, we outline our steps to ensure the robustness of our findings.

3.1. Efficiency Scores

Tables 3 and 4 show the efficiency scores based on CRS and VRS. The average initial technical efficiency scores are 0.89 (CRS) and 0.96 (VRS), indicating good performance of JVCBs and FBs during 2011–2020. Next, we apply Simar & Wilson's (2007) method. The average double-bootstrap technical efficiency scores are 0.83 (CRS) and 0.94 (VRS). The efficiency scores were the lowest in 2014 at 0.78 (CRS) and 0.91 (VRS), and then rose to 0.80 (CRS) and 0.94 (VRS) in 2016. The VRS measures pure technical efficiency, which reflects management skills; notably, its average score is higher than that of the CRS, which measures overall technical efficiency. As shown in Table 4, the HSBCVN had the lowest average CRS (0.69) and highest average VRS (0.96). SHINHANVN and HONGLEONG achieved the highest average CRS (0.98), whereas the VID bank had the lowest average VRS (0.93).

Table 3: Average technical efficiency scores of all JVCBs and FBs from 2011 to 2020

Year	CRSEff	CRSEff biased correct	CRSEff lower bound	CRSEff upper bound	VRSEff	VRSEff biased correct	VRSEff lower bound	VRSEff upper bound
2011	0.91	0.83	0.78	0.9	0.98	0.96	0.9	0.98
2012	0.89	0.83	0.78	0.89	0.96	0.94	0.89	0.96
2013	0.84	0.81	0.78	0.84	0.91	0.9	0.86	0.91
2014	0.81	0.78	0.76	0.81	0.93	0.91	0.88	0.93
2015	0.82	0.78	0.75	0.82	0.93	0.92	0.88	0.93
2016	0.85	0.8	0.76	0.84	0.96	0.94	0.91	0.96
2017	0.95	0.9	0.85	0.95	0.97	0.95	0.9	0.97
2018	0.94	0.88	0.82	0.94	0.99	0.96	0.9	0.99
2019	0.96	0.89	0.83	0.95	0.99	0.96	0.89	0.99
2020	0.94	0.84	0.77	0.93	1	0.96	0.88	0.99

Note: Source: Financial statements of JVCBs and FBs in Vietnam from 2011 to 2020.

Table 4: Bank-wise average technical efficiency scores. Note: (*) Banks with data less than 10 years

ID	State	CRSEff	CRSEff bias corrected	CRSEff lb	CRSEff ub	VRSEff	VRSEff bias corrected	VRSEff lb	VRSEff ub
1	INDOVINA	0.86	0.83	0.79	0.86	0.92	0.9	0.85	0.92
2	VID	0.94	0.91	0.87	0.93	0.95	0.93	0.9	0.95
3	HSBCVN	0.74	0.69	0.64	0.74	0.98	0.96	0.91	0.98
4	SHINHANVN	0.98	0.9	0.84	0.97	0.99	0.96	0.9	0.99
5	HONGLEONG (*)	0.98	0.88	0.81	0.98	0.98	0.96	0.88	0.98
6	ANZVN (*)	0.93	0.86	0.81	0.93	0.99	0.96	0.9	0.99
	Average	0.89	0.83	0.79	0.89	0.96	0.94	0.89	0.96

Note: Source: Financial statements of JVCBs and FBs in Vietnam from 2011 to 2020.

3.2. Regression Results for Environmental Variables

We regress the bias-corrected DEA efficiency scores on national governance indicators and bank characteristics using Equation 3 with random effects. We run panel data regressions, each of which includes only one national governance variable to avoid multicollinearity, as these variables measure closely related aspects of the macro environment and tend to be highly correlated. The results are summarised in Table 5 reports.

Table 5: Regression results of national governance variables

	CC	GE	PS	RQ	RL	VA	CPI
Panel A: CRS-BC							
Intercept	1.0374**	1.3878***	1.1647***	1.8526***	1.5438***	0.7034	0.9817***
	(0.4202)	(0.3889)	(0.4104)	(0.3954)	(0.3838)	(0.5972)	(0.3341)
Governance	-0.0222	0.2872***	-0.1491	0.3465***	0.1877***	-0.2904	0.0240***
	(0.2164)	(0.0989)	(0.1235)	(0.0842)	(0.0532)	(0.3707)	(0.0053)
LNTA	0.2467	1.6017	0.5711	1.7768	1.9114*	0.1828	1.9636*
	(1.2870)	(1.1903)	(1.2074)	(1.0827)	(1.1557)	(1.2049)	(1.0578)
ROA	-0.0051	-0.0287	-0.0127	-0.0523**	-0.0366	-0.0097	-0.0564**
	(0.0266)	(0.0256)	(0.0269)	(0.0253)	(0.0250)	(0.0270)	(0.0246)
LA	-0.3289**	-0.3062**	-0.3242**	-0.1910	-0.2377*	-0.2895*	-0.1663
	(0.1589)	(0.1429)	(0.1535)	(0.1365)	(0.1399)	(0.1641)	(0.1334)
DTA	0.2808**	0.3533***	0.3103**	0.3648***	0.3090**	0.2693*	0.3395***
	(0.1411)	(0.1286)	(0.1377)	(0.1187)	(0.1219)	(0.1385)	(0.1143)
EXTA	-2.3675	-2.1891	-1.8647	-2.0304	-3.3219*	-2.5013	-2.5641
	(2.0046)	(1.8119)	(1.9870)	(1.6798)	(1.7664)	(1.9784)	(1.6305)
N	50	50	50	50	50	50	50
Adjusted R^2	0.2625	0.3833	0.2865	0.4706	0.4282	0.2726	0.5007
Panel B: VRS-BC							
Intercept	0.5355***	0.6251***	0.5909***	0.7516***	0.6573***	0.1945	0.5469***
	(0.1848)	(0.1842)	(0.1826)	(0.1967)	(0.1875)	(0.2542)	(0.1755)
Governance	-0.0426	0.0576	-0.0434	0.0838**	0.0380	-0.3050*	0.0037
	(0.0952)	(0.0468)	(0.0549)	(0.0419)	(0.0260)	(0.1578)	(0.0028)
LNTA	0.1619	0.5132	0.3317	0.6097	0.5782	0.1349	0.5050
	(0.5659)	(0.5639)	(0.5371)	(0.5387)	(0.5646)	(0.5129)	(0.5556)
ROA	0.0238**	0.0190	0.0215*	0.0123	0.0173	0.0190*	0.0159
	(0.0117)	(0.0121)	(0.0120)	(0.0126)	(0.0122)	(0.0115)	(0.0129)
LA	-0.0740	-0.0748	-0.0777	-0.0459	-0.0609	-0.0353	-0.0548
	(0.0699)	(0.0677)	(0.0683)	(0.0679)	(0.0684)	(0.0699)	(0.0701)
DTA	-0.0175	0.0021	-0.0041	0.0077	-0.0067	-0.0271	-0.0034
	(0.0620)	(0.0609)	(0.0612)	(0.0591)	(0.0595)	(0.0589)	(0.0601)
EXTA	1.5189*	1.6089*	1.7167*	1.6534**	1.3800	1.4059*	1.5447*
	(0.8814)	(0.8584)	(0.8839)	(0.8358)	(0.8629)	(0.8422)	(0.8564)
N	50	50	50	50	50	50	50
Adjusted R^2	0.1060	0.1324	0.1147	0.1783	0.1444	0.1736	0.1365

*Note: This table shows the estimated coefficients of the seven national governance variables in the panel regression model with random effects while controlling for bank characteristics. The dependent variables are CRS-BC and VRS-BC, or the bias-corrected bank efficiency measures. Each regression run only includes one national governance variable (e.g., in the CPI column, the governance variable is CPI). All the variables are explained in Appendix A. Standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.*

When CRS-BC is the dependent variable (Panel A), the coefficients are positive and statistically significant at 1% for four national governance variables (CPI, GE, RQ, and RL); that is, improved *national governance* enhances bank efficiency. This is consistent with the results of previous studies (Figueira et al., 2009; Pasiouras et al., 2009; Lozano-Vivas & Pasiouras, 2010; Chortareas et al., 2013; Kamarudin et al., 2016; Osei-Tutu, 2021;). RQ has the largest impact, whereas the effect of corruption (CPI) is the smallest. Although the other variables (CC, PS, and VA) counterintuitively show negative coefficients, none are statistically significant. When VRS-BC is the dependent variable (Panel B), only two governance variables are statistically significant (RQ at 5% and VA at 10%). While VA shows a negative coefficient, RQ's coefficient is positive, consistent with the literature. However, its magnitude is smaller than that in CRS-BC.

The adjusted R^2 is substantially higher for the CRS-BC than for the VRS-BC; even the lowest value for the CRS-BC (0.26 for CC) is still much higher than the highest value for the VRS-BC (0.18 for RQ). National governance demonstrates considerable explanatory power for bank efficiency, with adjusted R^2 ranging from 0.11 (VRS-BC, CC, and PS) to as much as 0.5 (CRS-BC, CPI). RQ offers the best explanatory power, showing the highest adjusted R^2 for VRS-BC (0.18) and a close runner-up for CRS-BC (0.47). The control variables for bank characteristics are often insignificant, except for LA, DTA (CRS-BC), and EXTA (VRS-BC). The intercept is almost always significant at the 1% level, except for VA.

Thus, we intuitively find that banks should become more efficient if national governance improves. A more favourable macro environment should facilitate banks' operations so that they can utilise their inputs (e.g., deposits and staff) more efficiently for greater outputs (e.g., loans and securities). This is especially vital for JVCBs and FBs because the macro environment strongly influences many of their crucial decisions, such as entry and exit (whether to enter and do business in the country or leave if already there). RQ seems to be the most important in national governance, as evidenced by its largest coefficient and adjusted R^2 overall. Interestingly, the CRS-BC efficiency measure seems much better at reflecting governance impacts (many significant results) than the VRS-BC. Finally, some bank characteristics (e.g., loans, deposits, and staff expenses relative to assets) can help explain bank efficiency.

3.2.1 Implications

Our results show that merely focusing on the economic conditions of the target market is not enough for foreign institutions when they are planning their expansion. National governance is also important. It can make or break their business, and hence, requires due diligence and careful scrutiny. Even during their operations in the country, JVCBs and FBs should constantly monitor the macro environment and their own efficiency so that they can make timely decisions about future business (e.g., stay, scale up/down, or leave). Meanwhile, participants in financial markets (e.g., investors, traders, and analysts) should consider national governance when analysing the performance of JVCBs and FBs to make the most informed decisions. Further research could investigate: (i) other aspects of governance that have not yet been studied, (ii) different types of banks, (iii) other countries (developing or even developed), and (iv) different periods (perhaps longer and more recent). These studies can help us develop a more multifaceted and comprehensive understanding of how national governance affects bank efficiency.

3.3. Robustness

Several steps were taken to increase the robustness of the results. First, regarding bank characteristics as control, initially we had 11 candidates: profit before tax over asset (ROA), profit before tax over equity (ROE), total asset (LNTA), loan loss provision (LLPL), equity over asset (ETA), deposit over asset (DTA), loan over asset (LA), staff expense over asset (EXTA), number of years since establishment (LNAGE), number of branches (LNBR) and non-performing loans (LNPL). However, they tend to be highly correlated (Appendix B). The absolute values of the correlation coefficients even exceed 81%. The only way to eliminate multicollinearity is to use only one variable, which is insufficient to control for the relevant effects. Hence, we use a reasonable number of variables (five), including ROA, LNTA, DTA, LA, and EXTA. They are less correlated, but still reflect various important aspects of operations (bank size, liquidity, and expenses).

Second, before conducting the regression, we ensured data stationarity. For extra robustness, we employ several tests from Im et al. (2003) and Maddala & Wu (1999), and multiple tests in Choi (2001). The null hypothesis of a unit root is always rejected at the 1% level, which confirms stationarity.

Third, we apply the Hausman specification test, including the original version in Hausman (1978) and an alternative version in Wooldridge (2010), to choose fixed- or random-effects models. The null hypothesis is no correlation between the explanatory variables and error terms. These results favour random effects models which can generate lower variances in estimation than fixed-effects models (Wooldridge, 2010). Moreover, the absence of a correlation between the explanatory variables and error terms indicates that these variables are not endogenous (i.e., exogenous and not influenced by other variables in the system).

For completeness, we also estimate fixed-effects models (see Appendix C). When CRS-BC is the dependent variable, the results from the random- and fixed-effects models are relatively similar in terms of the coefficient signs of national governance variables. Nevertheless, these coefficients are only significant at the 5% level for the fixed-effects models (compared to 1% for random-effects models), suggesting that random effects may be better at reflecting the influence of national governance. When VRS-BC is the dependent variable, the national governance coefficients are not statistically significant with fixed effects, while some are significant with random effects. Moreover, the negatively adjusted R^2 of the fixed effects models indicates that random effects may be a more appropriate setting.

Finally, we consider endogeneity concerns, which is the potential simultaneous mutual effects between the dependent (bank efficiency) and independent variable (national governance). This could be a problem if bank efficiency affects and is affected by national governance. However, bank efficiency is a firm-level variable; therefore, it should be affected by country-level national governance rather than vice versa. Therefore, there should be no problem with the feedback loop from the dependent to independent variables.

4. Conclusion

Using Simar & Wilson's (2007) double bootstrap method, we find that the average technical efficiency score for the JVCBs and FBs are 0.83 (CRS) and 0.94 (VRS). These more accurate estimates indicate lower efficiency than the traditional method. The efficiency scores are then regressed on environmental variables to identify the main determinants of efficiency. Most governance indicators are statistically significant and show that better governance increases efficiency, with RQ having the greatest impact and explanatory power. This is consistent with previous studies (Denis & McConnell, 2003; Grosvold & Brammer, 2010) in which national institutional factors strongly influence corporate behaviours and practices.

If governments want to promote the healthy growth of foreign investment in the banking sector (via JVCBs and FBs), they should improve national governance and create a favourable environment for outsiders to enter and do business successfully. RQ (the government's ability to adopt robust policies beneficial for the private sector) seems the most important; therefore, governments need to focus even more on this area, including both general and banking-specific regulations. Solid national governance should help (foreign) banks to achieve superior efficiency and profitability. In turn, this will strongly encourage existing institutions to stay in the country and attract new players from abroad. This is especially crucial, given the role of JVCBS and FBs in the economy. Hasan & Marton (2003) found that the involvement of JVCBs and FBs with domestic institutions helps build a strong and efficient banking system since banks with foreign ownership are associated with higher efficiency. However, strong governance does not always mean 'strict' governance because excessive restrictions and interventionist policies may obstruct banks' operations and make them less efficient (Barth et al., 2004; Chortareas et al., 2012; Barth et al., 2013).

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Appendices

Appendix A.

Notations, measures, and expected effects of the independent and control variables on bank efficiency.

Variables	Notations	Measures	Expected effect
Dependent variables			
	CRS-BC	Constant returns to scale bias-corrected	
	VRS-BC	Variable returns to scale bias-corrected	
Bank characteristics variables			
	Bank size (LNTA)	Natural logarithm of total assets	+
	ROA	Net profits before taxes/total assets	+
	Liquidity (LA)	Loans/assets	-
	DTA	Deposits/assets	+
	EXTA	Staff expense/assets	-
National governance variables			
	CPI	Corruption perception index	+
	CC	Corruption control	+
	GE	Government effectiveness	+
	PS	Political stability and absence of violence	+
	RQ	Regulatory quality	+
	RL	Rule of law	+
	VA	Voice and accountability	+

Appendix B.

Correlation matrix of the control variables for bank characteristics.

	ROA	ROE	LNTA	LLPL	ETA	DTA	LA	EXTA	LNAGE	LNBR	LNPL
ROA	1.0000	-	-	-	-	-	-	-	-	-	-
ROE	0.5161	1.0000	-	-	-	-	-	-	-	-	-
LNTA	0.0507	0.6639	1.0000	-	-	-	-	-	-	-	-
LLPL	0.0770	0.0457	-0.2016	1.0000	-	-	-	-	-	-	-
ETA	0.2944	-0.4929	-0.7306	-0.0854	1.0000	-	-	-	-	-	-
DTA	-0.1260	0.5580	0.8127	-0.0108	-0.7918	1.0000	-	-	-	-	-
LA	-0.2010	0.0559	0.0899	0.3568	-0.4828	0.2033	1.0000	-	-	-	-
EXTA	0.3784	0.2325	-0.1867	0.0077	0.3821	-0.1554	-0.4764	1.0000	-	-	-
LNAGE	-0.4020	-0.1797	0.2096	-0.0513	-0.5666	0.2360	0.6510	-0.6336	1.0000	-	-
LNBR	-0.1440	0.2203	0.5844	-0.0374	-0.5561	0.3989	0.5196	-0.5985	0.5425	1.0000	-
LNPL	-0.2758	0.4410	0.7124	0.0896	-0.6988	0.7115	0.4041	-0.1388	0.2683	0.5108	1.0000

Appendix C.

Regression results for the national governance variables. This table shows the estimated coefficients of the seven national governance variables in the panel regression model with fixed effects, while controlling for bank characteristics. The dependent variables are CRS-BC and VRS-BC, which are bias-corrected bank efficiency measures. Each regression run only includes one national governance variable (e.g., in the CPI column, the governance variable is CPI). Standard errors are indicated in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

	CPI	CC	GE	PS	RQ	RL	VA
Panel A: CRS-BC							
Governance	0.0152**	0.0160	0.1988**	-0.0464	0.2053**	0.1283**	0.2620
	(0.0061)	(0.1856)	(0.0893)	(0.0986)	(0.0975)	(0.0623)	(0.3046)
LNTA	0.0228	0.1018**	0.0843**	0.0957**	0.0366	0.0624	0.1225**
	(0.0502)	(0.0454)	(0.0409)	(0.0446)	(0.0507)	(0.0447)	(0.0499)
ROA	2.7279**	2.8206*	3.0111**	2.8075**	2.3808*	2.6360**	3.3071**
	(1.2128)	(1.4478)	(1.2410)	(1.3349)	(1.2598)	(1.2515)	(1.4599)
LA	0.9476***	1.0988***	1.0435***	1.0916***	0.9430***	0.9050***	1.1694***
	(0.2096)	(0.2294)	(0.2065)	(0.2214)	(0.2189)	(0.2269)	(0.2363)
DTA	-0.2755*	-0.3400*	-0.4048**	-0.3312*	-0.3271**	-0.3842**	-0.3715**
	(0.1543)	(0.1705)	(0.1582)	(0.1679)	(0.1566)	(0.1586)	(0.1706)
EXTA	-8.0691***	-10.6501***	-9.3885***	-10.3696***	-7.7407**	-8.8968***	-11.3480***
	(2.6600)	(2.7303)	(2.5664)	(2.7545)	(2.8723)	(2.6681)	(2.8076)
N	50	50	50	50	50	50	50
Adjusted R^2	0.4971	0.3879	0.4772	0.3924	0.4690	0.4659	0.4030
Panel B: VRS-BC							
Governance	-0.0029	-0.0992	0.0060	0.0048	0.0035	-0.0173	-0.1905
	(0.0034)	(0.0951)	(0.0504)	(0.0517)	(0.0546)	(0.0347)	(0.1571)
LNTA	0.0609**	0.0391	0.0455*	0.0465*	0.0449	0.0511**	0.0301
	(0.0285)	(0.0232)	(0.0231)	(0.0234)	(0.0284)	(0.0249)	(0.0257)
ROA	1.0753	0.7707	1.0738	1.0631	1.0599	1.0851	0.6784
	(0.6899)	(0.7420)	(0.7008)	(0.6993)	(0.7060)	(0.6963)	(0.7528)
LA	0.2739**	0.2153*	0.2444**	0.2461**	0.2433*	0.2713**	0.1910
	(0.1192)	(0.1176)	(0.1166)	(0.1160)	(0.1227)	(0.1263)	(0.1218)
DTA	-0.1061	-0.0787	-0.0962	-0.0949	-0.0940	-0.0879	-0.0695
	(0.0878)	(0.0874)	(0.0893)	(0.0880)	(0.0877)	(0.0882)	(0.0880)
EXTA	-2.1942	-1.5331	-1.6671	-1.7302	-1.6549	-1.9365	-1.1768
	(1.5132)	(1.3992)	(1.4492)	(1.4430)	(1.6096)	(1.4846)	(1.4477)
N	50	50	50	50	50	50	50
Adjusted R^2	-0.2512	-0.2358	-0.2815	-0.2817	-0.2819	-0.2712	-0.2202