Is there a relationship between information search and product experience ratings?: A case study of the Vietcombank mobile banking app

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Abstract

This paper examines the relationship between information search and product experience ratings in a case study of the Vietcombank mobile banking app. The Python programming language was used to scrape the Vietcombank mobile banking app ratings from Google Play, and the search volume for the terms "Vietcombank" and "VCB" was extracted from Google Trends. Data analysis was conducted using the VAR-Granger, ordinary least squares, and copula approaches, based on data collected from December 2012 to April 2023. The estimation results provide empirical evidence supporting the relationship between information search and product experience ratings. Specifically, the findings indicate the following: (1) a unidirectional causality relationship from the quantity of searches for "Vietcombank" to the app ratings; (2) a bidirectional causality relationship between searches for the term "VCB" and app ratings; 3) a positive influence of search volume on app ratings; (4) an upper tail dependency between the search volume of the term "Vietcombank" and the app ratings; and (5) no tail structural dependence structure between the search volume of the term "VCB" and the app ratings.

Keywords: *Google search, App ratings, Vietcombank, VAR-Granger, Copula*

JEL classification: O30, G20

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1. INTRODUCTION

Numerous publications have confirmed that, when internet users seek knowledge, they typically rely on search engines and search for relevant keywords (Bijl et al., 2016; Mellon, 2013). This information search behavior, which involves capturing keywords and is measured by search volume, is typically recorded by most of the leading search engines such as Google, Bing, and Yahoo.

In modern society, smartphones have become indispensable devices that are constantly by our side. It has become the center of many different activities, allowing us to easily call a taxi, book a room, purchase a ticket, and more through dedicated apps. The development of smartphones has significantly contributed to the growth of mobile apps specifically designed for these devices. In this digital era, the act of downloading and installing apps on smartphones represents consumption behavior in relation to high-tech products provided by a developer (Genc-Nayebi & Abran, 2017; Kapoor & Vij, 2020; Sun et al., 2019). The reviews and ratings found on app stores such as the App Store or Google Play reflect the level of customer satisfaction regarding their product experience.

Based on users' information search and app usage behavior, we have observed that users commonly undertake two actions when installing an app on a smartphone: (1) gathering and acquiring relevant information about the app through searching for related keywords, followed by providing ratings, and (2) quickly reviewing past ratings while simultaneously searching for related keywords to gain additional insights. With these observations, we are interested in investigating whether a relationship exists between information search and app ratings.

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Table 1. Market share of mobile operating system

Year	Vietnam			Worldwide		
	Android (%)	**iOS (%)**	**Others (%)**	**Android (%)**	**iOS (%)**	**Others (%)**
2018	59.35	36.66	3.99	75.45	20.47	4.08
2019	59.52	38.67	1.81	75.47	22.71	1.82
2020	62.71	36.2	1.09	73.06	26.28	0.66
2021	65.51	33.85	0.64	71.89	27.34	0.77
2022	70.62	28.96	0.42	71.47	27.85	0.68
2023	69.05	30.58	0.37	70.57	28.74	0.69

Source: https://gs.statcounter.com/os-market-share/mobile/worldwide#yearly-2009-2023 (Retrieved: 09 May 2023)

In this study, we have selected the Joint Stock Commercial Bank for Foreign Trade of Vietnam (Vietcombank), a prominent commercial bank in Vietnam known for its assets, capital, and profitability, to investigate the relationship between information search and app ratings. We chose Vietcombank for several reasons. Firstly, the Vietnamese context is suitable for developing smartphones and mobile apps. Numerous market reports have confirmed that Asia is experiencing a significant growth rate in the smartphone market compared to other regions worldwide. According to Statista 2022, Vietnam, an emerging country in Southeast Asia, has shown rapid economic growth and the highest smartphone penetration rates in Asia. In 2022, approximately 73.5% of adults in Vietnam were using smartphones, and there was a 97.6% share of internet users who owned smartphones. Additionally, Vietnam has a robust infrastructure that supports the development of smartphones. Additionally, Vietnam is putting into action its National Strategy for the Development of the Digital Economy and Digital Society through 2025, with a focus on 2030, to improve the environment for the advancement of smartphones. Secondly, digitalization in the banking industry is rapidly advancing in Asia, including Vietnam, leading to competition among commercial banks in developing mobile banking apps. Vietcombank, as a leading commercial bank in Vietnam, has emerged as a pioneer in this field. In 2001, Vietcombank introduced the first version of its mobile app called VCB-iB@nking, and since then, it has introduced several iterations of digital banking apps that are regularly updated to provide an optimal user experience. As of April 2023, Vietcombank offered four distinct types of digital banking apps: VCBDigibank for personal use, VCBDigiBiz and VCB-iB@nking for corporate use, and VCB CashUp for institutions. Furthermore, according to Vietcombank's annual reports, VCBDigibank for personal use has become the most popular mobile banking app, catering to a vast customer base. The bank continues to prioritize the development of this app as part of its strategy to become a leading retail bank. At the same time, when considering market trends globally and in Vietnam, Android and iOS are the most popular mobile operating systems, as reported by Statcounter. Android consistently holds the highest market share, followed by iOS (detailed in Table 1). Consequently, this study focuses on VCBDigibank for personal use, specifically the version available on Google Play, which operates on the Android platform.

In this investigation, we sought to examine the connection between information searches and product experience ratings, focusing specifically on Vietcombank's mobile banking apps. To do this, we use Google Trends to collect data on the search frequency of terms like "Vietcombank" and "VCB" (Pham et al., 2021). Google Trends is an important tool for recording and analyzing the popularity of search keywords on a scale of 0 to 100, known as the Google search index. Several studies, such as Ekinci and Bulut (2021) and Mellon (2013), have utilized Google Trends to investigate the behavior of internet users during keyword searches. Moreover, we also mention the importance of brand names in consumer search behavior (Peterson and Merino, 2003), and in this case, "Vietcombank" and "VCB" are two terms used consistently in Vietcombank's marketing campaign. Therefore, we use these terms for quantitative analysis. The objective of the study is to leverage Google Trends to analyze the behavior of internet users when searching for information about Vietcombank. Next, we will investigate the relationship between this behavior and the rating of Vietcombank's mobile app on Google Play.

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This study adds fresh knowledge regarding the connection between information search and product experience rating, particularly for Vietcombank's mobile banking app. This has significant value for bank management since user search and ranking behavior play a significant role in enhancing app quality and offering the greatest customer experience, which helps to increase the bank's operational efficiency.

2. THEORETICAL BACKGROUND

Research framework

Initially, Nelson (1970) proposed a theory that explored the relationship between information and consumer behavior. We have created a framework to investigate the relationship between information search and product experience ratings, two essential elements of the information side, in the process of choosing to acquire a mobile banking app. This framework is based on the premise that information is the driving force behind decision-making. This mobile banking app is a high-tech product offered by a commercial bank in the digital era. We are interested in if there is a relationship between information search and product experience ratings.

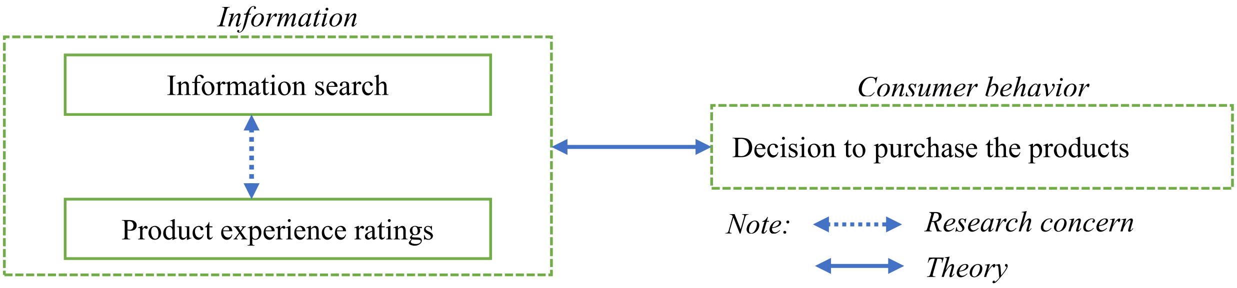

Figure 1. Research concern and relevant theory
Source: The authors

First of all, the concept of consumer information search behavior that DeSarbo and Choi (1998) developed forms the foundation of our study. Internal and external information searches are the two elements that make up this idea. The retrieval of knowledge from memory is referred to as an internal information search, and it triggers an external information search. A number of factors influence and complicate the information search process. Consumer knowledge has an impact on internal information searches, whereas data accessibility and search engine tools are key factors in external information searches. Making educated customer decisions is the ultimate objective. This study focuses in particular on how searching for external information influences customer choice while using mobile banking apps.

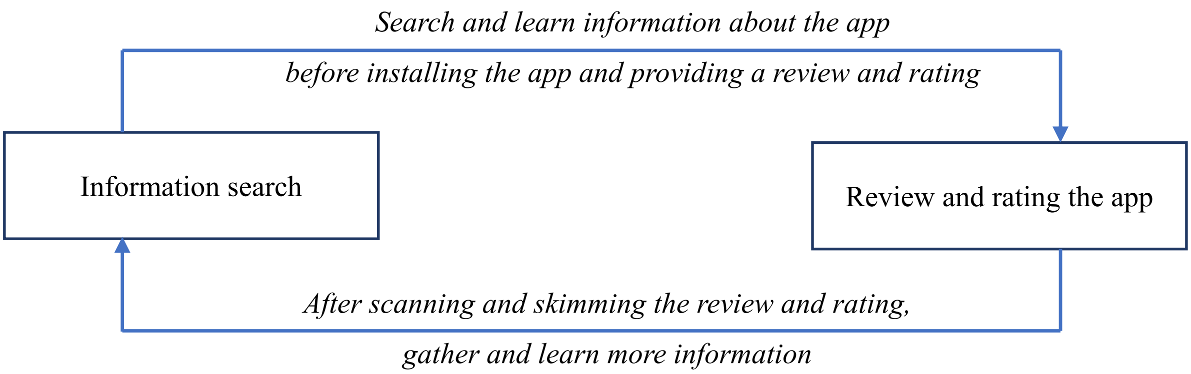

Figure 2. Research framework
Source: The authors

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Secondly, in the digital era, online product experience reviews and ratings have become a crucial channel for reducing consumer uncertainty (Eslami et al., 2018; Sun et al., 2019). In the context of mobile banking app consumption, we propose that users tend to read and gather information about the app's reviews before deciding to install and experience it. These reviews are commonly found on popular platforms such as the App Store or Google Play. Consequently, the review content and ratings of the app play a paramount role in the decision-making process of users.
Information searches and product experience reviews are significant factors that play a crucial role in consumer behavior, particularly in the banking sector, where commercial banks are actively competing to offer mobile banking apps to customers. However, to the best of our knowledge, the relationship between these two factors has not been clearly elucidated in existing publications. The interaction between these factors can be illustrated as shown in Figures 1 and 2.
Moreover, consumers intending to use financial products through a mobile banking app prefer to gather information about the app and the bank that owns it before deciding to install it on their mobile phones. In the digital era, using search engines to search for keywords is the most effective way to learn and gather information. It follows that if people have complete faith in the bank and the app, they proceed to download, install, and utilize the app. Following their usage, app developers typically request users to provide reviews and ratings. Therefore, we argue that there is a correlation between information search and app experience ratings.
On the other hand, when scanning and skimming through the app's reviews and ratings, customers tend to gain insights into both the app and the bank that owns it. By using search engines, they can access additional information. Hence, there is an existing correlation between app ratings and keyword search behavior.

Relevant publication review

Engineering technology has experienced substantial global booms, revolutions, and developments recently. Nowadays, instead of directly interacting with providers to obtain goods and services, customers look for information and first try out goods and services online (Jimenez et al., 2019). For instance, when buying, customers frequently rely on online evaluations or suggestions from other customers to decide what to buy (Genc-Nayebi & Abran, 2017). Google search patterns have been shown to be a reliable predictor of public interest (Zhao et al., 2018). Google is an unequaled behemoth in a world where knowledge is power, giving users quick access to a variety of information. With a market share of more than 86%, it is clear that Google currently holds a dominant position in the search engine industry, and people are likely to use "Google" while looking for information (Jimenez et al., 2019). In January 2023, Google Search had a market share of 84.69% among the top and most popular search engines used globally(Statista, 2023).[1]
Furthermore, according to Shinde (2022), individuals' daily lives are constantly influenced by the opinions and views of others. The Internet not only affects human social life but also contains more and more information related to people's views and emotions. Customer reviews posted online, in particular, can have a favorable or negative effect on the standard of a service and the purchase habits of prospective clients (Leem & Eum, 2021). The primary uses of text mining and business-related information analysis are to comprehend user emotions or spot developing issues in blog posts, comments, and reviews.
Positive evaluations help businesses make more money since customers frequently read them before selecting a service, lodging option, or restaurant (Leem & Eum, 2021). For example, Luca (2016) found that adding a star on Yelp resulted in a 5-9% increase in profits for a restaurant. Meanwhile, Salazar et al. (2018) found that apps downloaded through Google ranked poorly overall but scored higher in aspects such as "functionality" than top-rated apps. Their research provides reliable information that readers can use based on their own criteria and all aspects discussed, rather than recommending specific

[1] https://www.statista.com/topics/1001/google/#topicOverview

apps. Moreover, Gursoy (2019) conducted a review of papers introducing critical factors that influence information search behavior and online reviews in the hospitality sector. The study indicated that online reviews played a crucial role as the most important source in customers' information search behavior. Woo and Owen (2019) used Google Trends to forecast changes in the three categories of consumer goods: services, nondurable goods, and durable goods. They discovered that the volume of searches on Google could potentially reflect changes in consumption, and specific information searches could enhance the accuracy of consumption trend predictions in the United States. A substantial correlation between information search and the value of online reviews was found by Sun et al. (2019) using data from JD.com, one of the biggest marketplace sites in China. Additionally, they found that the search for product information and experience-related products was significantly influenced by various classifications of review informativeness.

Bei et al. (2004) conducted a study involving 1,355 students from a major university in Taipei, Taiwan, to investigate the connection between consumers' evaluations and internet information searches. The findings revealed that online information sources played a crucial role in shaping customers' product experiences. Customers demonstrated a preference for utilizing online information to express their experiences regarding product usage. The study also suggested that product experiences could potentially be shared and searched for in cyberspace. Mudambi and Schuff (2010) provided evidence that existing online reviews on electronic marketplace platforms such as Amazon were critical information sources for consumers during the pre-purchase decision stage. Similar to the results of Jiménez and Mendoza (2013), the study surveyed 178 customers about their purchase intention and the impact of online reviews for products. However, the sharp increase in online reviews has also led to skepticism, highlighting the need to classify the credibility of online review content.

Zhao et al. (2018) further stress the value of search engines in gaining access to product information on the Internet. Regardless of user reviews, consumers often seek additional information using search engines like Google before making a purchase, especially for experiential products. The use of search engines and online shopping has increased due to economic development, the Internet, and mobile technology. This study used Google search and sales data analyze the connection between search and product sales. The results show a positive effect between Google search and product sales, but retailer discounts and online reputation also influence consumer search behavior. These findings have important implications for the hotel industry and provide insight into consumer behavior in the online marketplace. Zhi Da et al. (2011) used the search visibility index (SVI) to study investor attentiveness. Their study shows that SVI attracts retail investor's attention and produces significant first-day profits. Between July 2012 and June 2017, 50 NIFTY equities were selected for analysis by Swamy and Dharani (2019). The findings demonstrate that frequent Google searches foretell favorable and noteworthy returns for the upcoming fourth and fifth weeks. The influence of declining volume in stock return analysis is less effective than the forecasting power of the Google search volume index. On the other hand, Bank et al. (2011) demonstrated that an increase in search queries tends to improve the liquidity and trading activity of stocks by using the company name rather than the ticker symbol and the GSVI. For the same 30 large stocks traded on the NYSE and NASDAQ, Vlastakis and Markellos (2012) found a strong correlation between information demand, volatility, and trading volume. Kim and Won (2018) discovered that while Google searches do not correspond with the current or forecast future anomalous returns, they can forecast volatility, movement, and higher trading volume. They noticed that future-oriented Google searches were more prevalent than those related to recent transaction activity.

Besides, Mahmood (2020) recognized that mobile and desktop apps have become more and more popular. The author argues that some apps have had billions of downloads, are highly appreciated, and are widely used. Modern information and communication technology cannot function without mobile apps. They provide users with rapid and simple access to the goods, services, data, and procedures they require. When consumers undertake internet searches for product information and compare the options available, they usually have access to dozens or hundreds of product reviews written by previous customers. As a result, the availability of Google Play has a significant impact on the app's marketability and success. The app rating system on Google Play is generally well-liked and open (Zhong & Michahelles, 2013). A trustworthy indicator of the app's popularity and quality, the system guarantees fairness and clarity in the rating process. In the Google Play store, each app's ranking is decided by the store itself (Mahmood, 2020). According to Sadiq et al. (2021), Google's overall app rating algorithm employs an intricate infrastructure to rate apps. One of the reasons Google's app store is so successful and surpasses rival app stores is because of its comprehensive rating system. The correlation between the Blackberry app store's pricing, ratings, and popularity was study by Finkelstein et al. (2017). They found a substantial correlation between user ratings and popularity, proving that users favor apps with higher ratings.

According to Jimenez et al. (2019), there are already more than 300,000 health apps on the market. These apps meet a variety of user needs, including those for managing chronic illness and losing weight, with diabetes being the most popular target disease. Government regulation of the majority of health applications is rare, and patients and medical staff have trouble selecting apps because there are not any official recommendations. Patients often use the Internet to search for recommendations for diabetes apps. When searching for health-related apps, Baxter et al. (2021) found that out of 19 apps, 7 (36.8%) were excluded and 12 (63%) were rated by three reviewers. This suggests that the number of high-quality health-related apps is somewhat few. The COVID-19 pandemic-related mobile health apps that Gonzales et al. (2023) found and reviewed were found via Google search as well. Using the mobile app rating scale (MARS), they discovered and assessed a total of 27 apps. Most apps are made to reduce COVID-19 exposure and improve health monitoring.

Additionally, maintaining current clients is less expensive than obtaining new ones; therefore, maintaining their loyalty is crucial (Alhejji et al., 2022). Because more people are reading internet evaluations and becoming more aware of them and their purchasing power, Zhang and Mao (2012) claim that the hotel business has seen a drop in customer loyalty. The Google Play store uses text ratings and reviews to understand user opinions and reviews. These reviews are considered trustworthy and helpful to other users when downloading or purchasing apps (Ranjan & Mishra, 2020). Mobile apps have been used by many organizations to meet user needs and boost customer happiness and loyalty. Examples include m-health, m-learning, and m-banking services, which are all related to the provision of healthcare and educational services. M-banking boosts consumers' time management skills through quick communication, information access, and accessibility from anywhere, improving both their quality of life and the effectiveness of banking operations (Malaquias & Hwang, 2016). In the banking industry, mobile banking is defined by Laukkanen and Kiviniemi (2010) as an interaction in which customers connect to the bank through a mobile device, such as a smartphone or a personal technical assistant number, within the context of a financial service offering made available by the bank as an added service by incorporating the features of absolute mobility. In many nations, internet and mobile technologies are developing quickly, which has resulted in the growth of online banking, particularly mobile banking (Alhejji et al., 2022).

In addition to these studies, other research conducted by Alanzi (2021), Prasad et al. (2019), Yakubu and Kwong (2021), and Zhang et al. (2020) indirectly implied a link between information search and product experience reviews, particularly in the context of the digital era, with the rapid growth of online reviews and the popularity of search engines.

Overall, the research shows that Google or Google Play have become increasingly popular for information searches as a result of technological advances. Its impact is taken into account in a variety of industries, including banking, securities, retail, and health. Google is crucial in facilitating easy access to banking and financial services and enhancing client loyalty and satisfaction. In the app industry and beyond, user experiences and decision-making are influenced by customer evaluations and ratings. However, prior research primarily examined how Google reviews and articles affected sales and profit as well as how Google Play reviews affected consumer decisions and trust in a company's online services. In this study, we contend that information searching and evaluating the quality of a product have a well-established relationship. Contrarily, users tend to have a better understanding of

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both the app and the bank that owns it when they skim and flick through app reviews and ratings. They are able to find more information by using search engines. It stems from the question of whether there is already a relationship between app ranking and keyword search activity.

3. METHODOLOGY

Data collection and data processing

The raw data used to calculate the variables were obtained from Google Trend and Google Play. The data was then transformed into logarithmic form to reduce the skewness of the measurement variable. The transformed variables were used for further analysis.

Customers who have downloaded and used the Vietcombank app were asked to rate and review the app and service. The rating scale ranged from the lowest level of satisfaction (1 star) to the highest level of satisfaction (5 stars). The raw data of the Vietcombank app ratings was initially extracted from Google Play using the Python programming language through the Azure Data Studio. The average rating score (average rating stars) was then calculated. This presented the product experience ratings variable.

Google Trend provided the search volume of related terms such as “Vietcombank,” “VCB,” “Ngân hàng Ngoại thương,” and “Ngân hàng Ngoại thương Việt Nam” from January 2004 to April 2023. The raw data showed that the search volume index for the terms “Ngân hàng Ngoại thương” and “Ngân hàng Ngoại thương Việt Nam” seemed to be zero, so they were excluded from further analysis. The search volume of the terms “Vietcombank” and “VCB” presented the information search variables, which were used for analysis.

Our aim was to collect as much data as possible. However, we discovered that the first review and ratings for the Vietcombank app dated back to December 2012, while the Google search data began in January 2004. Therefore, to align the series, we decided to start the dataset from December 2012 and extend it until April 2023, representing the latest available collected data.

Table 2 presents the definitions and characteristics of variables in both their raw and transformed forms within the dataset. $Google_{mean}^{Raw.Vietcombank}$ is 61.512, which is higher than $Google_{mean}^{Raw.VCB}$ at 14.624 over time. This suggests that customers have a preference for the brand name “Vietcombank” over the abbreviation “VCB”. When searching for information about the bank, most customers use the term “Vietcombank”. During data collection, we observed that the Vietnamese terms “Ngân hàng Ngoại thương” and “Ngân hàng Ngoại thương Việt Nam” were rarely used in Google searches. Consequently, we did not include these terms in our data extraction. These characteristics of the Vietcombank variables align with the description provided in the study by Pham et al. (2021).

Table 2. Descriptive statistics

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
$Ratings^{Raw.Stars}$	The monthly average stars represent the ratings given by customers who share their experiences with the Vietcombank mobile banking app on Google Play	125	3.70245	.61475	2.73496	4.85670
$Ratings^{Stars}$	Logrithm of $Ratings^{Raw.Stars}$	125	1.29525	.16688	1.00612	1.58036
$Google^{Raw.Vietcombank}$	The monthly search volume index for the term “Vietcombank”, extracted from Google Trend	125	61.51200	4.51452	51	69
$Google^{Vietcombank}$	Logrithm of $Google^{Raw.Vietcombank}$	125	4.11652	.07432	3.93183	4.23411
$Google^{Raw.VCB}$	The monthly search volume index for the term “VCB”, extracted from Google Trend	125	14.62400	2.24206	10	18
$Google^{VCB}$	Logrithm of $Google^{Raw.VCB}$	125	2.67037	.15974	2.30259	2.89037

Source: The authors

RatingsStars is 3.702, which is higher than the average score on the 5-point scale (2.50). This suggests that customers are satisfied with their experience using the Vietcombank app, as their ratings are above average.

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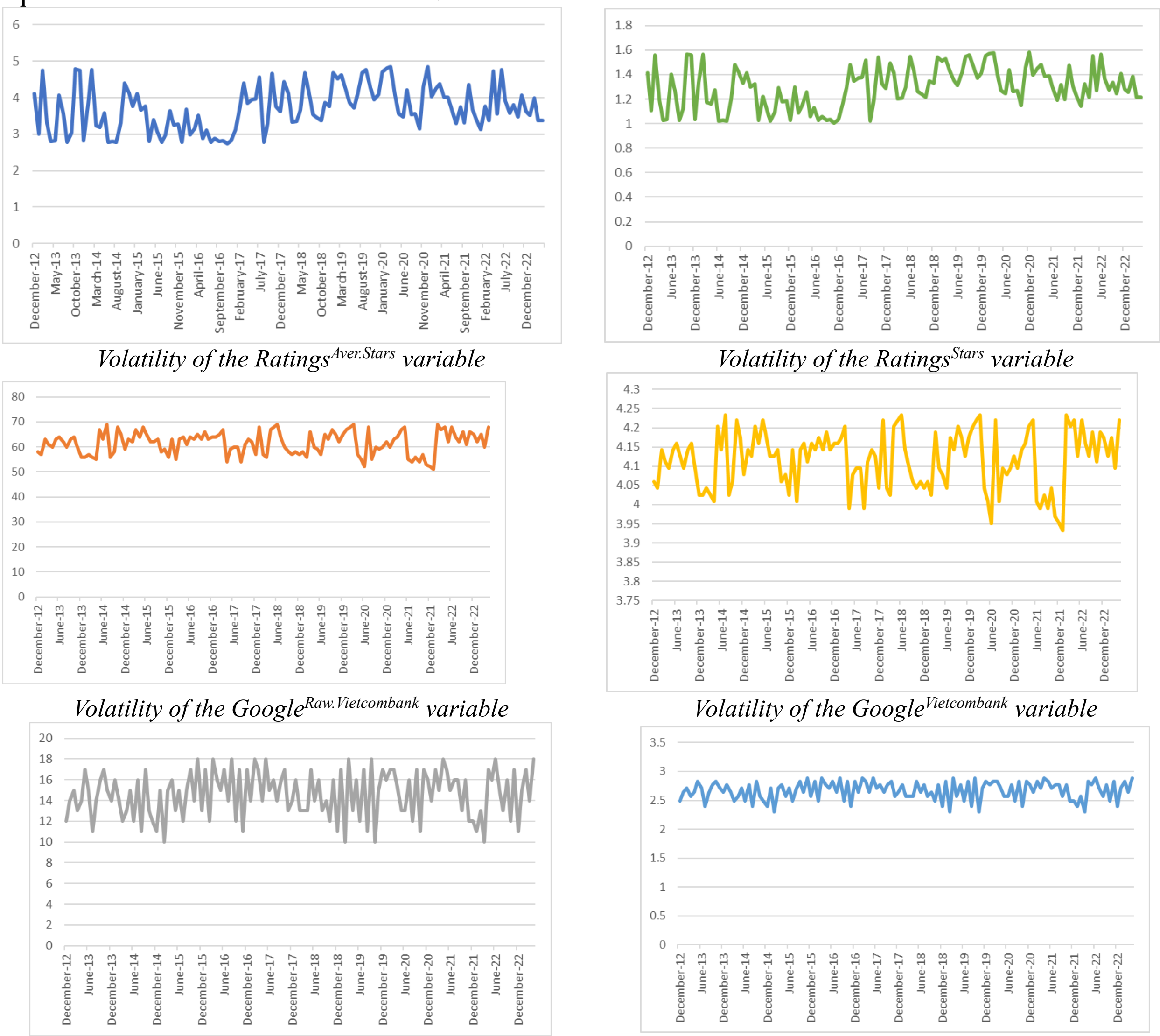
The standard deviations, minimum, and maximum values of Ratings^{Stars}, Google^{Vietcombank}, and Google^{VCB} indicate that these variables exhibit typical fluctuations, which may conform to the requirements of a normal distribution.



Volatility of the Ratings$^{Aver.Stars}$ variable

Volatility of the Ratings^{Stars} variable

Volatility of the Google$^{Raw.Vietcombank}$ variable

Volatility of the Google^{Vietcombank} variable

Volatility of the Google$^{Raw.VCB}$ variable

Volatility of the Google^{VCB} variable

Figure 3. The movement of variables

Source: The authors

Figure 3 displays the movement of variables in both raw and logarithmic forms, indicating a stochastic pattern. Based on our diagnosis, we observe the absence of any shocks that significantly impact the movement of the series. Therefore, we assert that the time period of the series is highly suitable for further analysis without the need for splitting.

Data analysis

This study investigates the connection between mobile banking app ratings at Vietcombank and information search (represented by Google^{Vietcombank} and Google^{VCB}). In order to get precise and trustworthy results, the authors used a wide range of quantitative techniques. To investigate the causal association between data series, the vector auto regression-Granger (VAR-Granger) method was specifically used. This technique enables one to ascertain whether information search impacts the efficiency of an app.

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Moreover, the ordinary least squares (OLS) method was used to study the impact of independent variables (information search) on the dependent variable (app ratings). This helps quantify how information searches affect app ratings.
The copula approach is also used in this study to check the relationship between two data series pairs. In addition to looking at the link between them, this aids in determining the relationship between information search and app ratings overall. To ascertain the cointegration of the data series, unit root tests were carried out prior to the application of the research methodologies. The long-term correlation of the variables must be ensured by doing this.
In total, the study conducted a detailed analysis with the goal of determining the relationship between information search and app ratings at Vietcombank. The VAR-Granger, OLS, and copula methods were applied to assess the importance and influence of these factors on users' decisions. The results of the study can provide important information on the correlation between information search and app ratings, helping Vietcombank better understand how to optimize the user experience and improve app placement on the market.

Proposed models

We provide three models to gauge the association between information search and Vietcombank's app ratings based on our data gathering capabilities and research methodology, as follows:

$$\text{Model 1: } Ratings^{Stars} = f(Google^{Vietcombank}) \quad (1)$$
$$\text{Model 2: } Ratings^{Stars} = f(Google^{VCB}) \quad (2)$$
$$\text{Model 3: } Ratings^{Stars} = f(Google^{Vietcombank}, Google^{VCB}) \quad (3)$$

Model 1 and Model 2 illustrate the relationship between the individual search volume of the term "Vietcombank" and "VCB" and the app ratings of Vietcombank. Model 3 demonstrates the contemporaneous relationship between the search volume of both the term "Vietcombank" and "VCB" and the app ratings of Vietcombank.

4. RESULTS AND DISCUSSION

Unit root test

Since the data is a time series, we initially conducted a unit root test for further analysis. We employed the Dickey-Fuller and Phillips-Perron methods to examine the stationarity of the series. Table 3 shows the estimation results of the unit root test.

Table 3. Unit root test

Variable	Dickey-Fuller test		Phillips-Perron test	
	t-statistics	Null hypothesis	t-statistics	Null hypothesis
$Ratings^{Stars}$	-7.022***	Reject	-7.208***	Reject
$Google^{Vietcombank}$	-7.769***	Reject	-7.877***	Reject
$Google^{VCB}$	-14.607***	Reject	-14.100***	Reject

The null hypothesis is defined as the presence of a unit root.

Source: The authors

The estimation results of the unit root test in Table 3 show that both methods confirm the rejection of the null hypothesis of a unit root presence in all series at level I(0) at a 1% confidence level. This indicates that all data series are stationary and can be used for further analysis. The necessity of conducting a unit root test on the first difference of the series has not yet arisen.

Lag-order selection

Next, the determination of optimal lags is crucial during the pre-estimation stage of time series data. In line with Huynh (2019) and Nasir et al. (2019), we employed the approach proposed by Lütkepohl (2005) to determine the optimal lags for the series. This approach provides four statistical values for selecting the optimal lags: final prediction error (FPE), Akaike's information criterion (AIC), Hannan and Quinn information criterion (HQIC), and Schwarz's Bayesian information criteria (SBIC). Ivanov and Killian (2001) recommended using AIC for monthly data in Vector auto regression, HQIC for data from a quarter with more than 120 observations, and SBIC for vector error correction models if these statistical values did not consistently identify the best lags. In our study, as we are using monthly data and planning to employ VAR-Granger for estimation, we give priority to AIC for selecting the optimal lag.

Table 4. The lag-order selection

Lags	Model 1				Model 2				Model 3			
	FPE	**AIC**	**HQIC**	**SBIC**	**FPE**	**AIC**	**HQIC**	**SBIC**	**FPE**	**AIC**	**HQIC**	**SBIC**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
0	.00015	-3.1397	-3.1209	-3.0935	.00069	-1.6051	-1.5863	-1.5588	3.3e-06	-4.1210	-4.0928	-4.0517
1	.00008*	-3.7123*	-3.6559*	-3.5736*	.00046	-2.0021	-1.9458	-1.8634	1.6e-06	-4.8128	-4.7002	-4.5355
2	.00009	-3.6621	-3.5683	-3.4311	.00040	-2.1598	-2.0660	-1.9287*	1.3e-06	-5.0512	-4.8541*	-4.5660*
3	.00009	-3.6758	-3.5445	-3.3524	.00037*	-2.2198*	-2.0884*	-1.8963	1.2e-06*	-5.0941*	-4.8126	-4.4010
4	.00009	-3.6489	-3.4710	-3.2330	.00038	-2.2031	-2.0342	-1.7872	1.3e-06	-5.0389	-4.6729	-4.1377

*Note: * is the suggestion of lag-order selection*
Model 1: $Ratings^{Stars} = f(Google^{Vietcombank})$, Model 2: $Ratings^{Stars} = f(Google^{VCB})$, and Model 3: $Ratings^{Stars} = f(Google^{Vietcomvbank}, Google^{VCB})$
Source: The authors

Table 4 presents the four statistical values used to select the optimal lags for each model. In Model 1, the consistency of the statistical values in columns 1, 2, 3, and 4 indicates that one (1) lag is suitable. Three (3) lags are recommended for Model 2 based on the FPE, HQIC, and AIC values in columns 5, 6, and 7. The consistency of the FPE and AIC values in columns 9 and 10, respectively, in Model 3 suggests that three (3) lags are adequate. For further analysis, these ideal delays are used.

Co-integration test

The Johansen co-integration method is employed to test for co-integration, following the selection of the optimal lags based on the dataset and the studies by Johansen (1988) and Lütkepohl (2005). This method is used to determine the presence of a long-run or short-run equilibrium relationship among the variables. The main statistical values in the Johansen test are the eigenvalue and trace statistic values, which are utilized to test the null hypothesis of the number of cointegration vectors at a 5% significance level.

Table 5. The co-integration test

Rank	Model 1				Model 2				Model 3			
	LL	Eigenvalue	Trace statistic	5% critical value	LL	Eigenvalue	Trace statistic	5% critical value	LL	Eigenvalue	Trace statistic	5% critical value
0	189.0986	-	88.0168	15.41	130.4776	-	35.1304	15.41	301.2096	-	38.6470	20.97
1	220.0861	0.3934	26.0419	3.76	141.4151	0.1642	13.2555	3.76	320.5331	0.2715	25.8391	14.07
2	233.1070	0.1894	-	-	148.0428	0.1030	-	-	333.4526	0.1909	11.5298	3.76
3									339.2175	0.0902	-	-

*Note: * is the suggestion of lag-order selection*
Model 1: $Ratings^{Stars} = f(Google^{Vietcombank})$, Model 2: $Ratings^{Stars} = f(Google^{VCB})$, and Model 3: $Ratings^{Stars} = f(Google^{Vietcomvbank}, Google^{VCB})$
Source: The authors

The results of the co-integration test are presented in Table 5. Eigenvalues and traces statistics were utilized to assess the statistical significance of the model.
Similar results with previous studies such as Onafowora and Owoye (2008) and Persyn and Westerlund (2008), both the eigenvalue and trace statistic values are equivalent in terms of statistical significance. We apply the trace statistic value to assess the null hypothesis in this work, following Huynh (2019) and Onafowora and Owoye (2008). As a result, we may reject the null hypothesis at any time because the values of the trace statistics in Table 5 consistently exceed 5% of the crucial value at all significance levels. This demonstrates how the three recommended models' and the three proposed models' long-term relationships between the variables are unstable. Based on the aforementioned findings, the

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research team has come to the conclusion that VAR estimation is a very acceptable method for doing further analysis on the relationships between the study's variables.

Granger causality estimation

In accordance with the research hypothesis and the aforementioned pre-estimation, we utilized the VAR-Granger method to examine the connection between Google search behavior and the app ratings of Vietcombank. The following justifies the VAR-Granger method's high regard as a tool for elucidating this relationship.

Firstly, the VAR-Granger method supports understanding and forecasting a time series's variables' connection. That is, it allows the research team to capture the correlation and impact between time series variables in the relationship between Google search activity and Vietcombank's app ranking. This helps understand the importance and influence of information search factors on Vietcombank's app ranking decision. Second, it takes into account the potential impact of latency on both the chain of interest and other related chains. That is, the VAR-Granger method not only considers the relationship between the variables in the present time but also takes into account the potential impact of latency from both the information search and the app rating chains. This aids the authors in determining how the past has affected the present and the future, as well as in understanding the mechanism and method by which independent variables have an impact. In addition to supporting multivariate time series analysis, the VAR-Granger approach also supports two-variable analysis. This made it possible for the study team to analyze the intricate relationships between the factors and determine how important they were in the connection between Google search activity and Vietcombank's app rating.

Table 6 presents the findings of the VAR-Granger estimate and contains thorough information on the relationship and effects of the research variable.

Table 6. Granger causality for variables

Model 1: *$Ratings^{Stars} = f(Google^{Vietcombank})$*				
Variable	$Ratings^{Stars}$	$Google^{Vietcombank}$	All	
$Ratings^{Stars}$	-	1.93	1.93	
$Google^{Vietcombank}$	10.245***	-	10.245***	
Model 2: *$Ratings^{Stars} = f(Google^{VCB})$*				
Variable	$Ratings^{Stars}$	$Google^{VCB}$	All	
$Ratings^{Stars}$	-	7.1728*	7.1728*	
$Google^{VCB}$	11.915***	-	11.915***	
Model 3: *$Ratings^{Stars} = f(Google^{Vietcomvbank}, Google^{VCB})$*				
Variable	$Ratings^{Stars}$	$Google^{Vietcombank}$	$Google^{VCB}$	All
$Ratings^{Stars}$	-	4.009	6.9144*	11.418*
$Google^{Vietcombank}$	6.9921*	-	10.428**	23.047***
$Google^{VCB}$	12.994***	12.057***	-	25.149***

*Note: *, **, and *** are the significant level at 10%, 5%, and 1%, respectively*
The null hypothesis is that the variable in the row does not Granger cause variable in the column
Source: The authors

Table 6 displays the statistical values of VAR-Granger estimation for the three proposed models, which are used to assess the causality relationship between variables. A unidirectional causality relationship exists from one variable to another if the statistical value is significant. Similarly, a bidirectional causality relationship between variables exists if there are both causal effects from one variable to another and causal effects in the opposite direction. Based on these criteria, we observed a significant unidirectional causality relationship from $Google^{Vietcombank}$ to $Ratings^{Stars}$ at the 1% significance level. This shows that the search activity on $Google^{Vietcombank}$ significantly affects the app ranking of Vietcombank. Furthermore, we found a bidirectional causality relationship between the pairs of variables $Google^{VCB}$ and $Ratings^{Stars}$, as well as between $Google^{Vietcombank}$ and $Google^{VCB}$. This suggests

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that there is a causal relationship that runs both ways between these variables and that the interactions and effects between them are rather complex. These results are convincing and offer significant proof in favor of the observation made in the causality test that there is a connection between information search and Vietcombank's app rating.

Ordinary least squares estimation

Based on the estimation results of the VAR-Granger approach and the selected optimal lags of the proposed models, we have formulated four regression models that illustrate the relationships between variables as follows:

Model 4: $Ratings_t^{Stars} = \propto + \sum_{j=0}^{1} \beta_j Google_{t-j}^{Vietcombank} + \mu_t$ (4)

Model 5: $Ratings_t^{Stars} = \propto + \sum_{j=0}^{3} \gamma_j Google_{t-j}^{VCB} + \mu_t$ (5)

Model 6: $Ratings_t^{Stars} = \propto + \sum_{j=0}^{3} \delta_j Google_{t-j}^{Vietcombank} + \sum_{j=0}^{3} \theta_j Google_{t-j}^{VCB} + \mu_t$ (6)

Model 7: $Google_t^{VCB} = \propto + \sum_{j=0}^{3} \delta_j Ratings_{t-j}^{Stars} + \mu_t$ (7)

Following the VAR-Granger analysis, we estimate the effect of the independent variables on the dependent variable using the OLS method. The estimation results of OLS, presented in Table 7, indicate that all four models are statistically significant at the 1% level (see the detailed statistics row). This demonstrates that in the four estimated models, the independent factors strongly contribute to the variation of the dependent variables. The independent variables may explain between 7.50% and 22.73% of the variation in the dependent variables across the four estimation models. However, much of the remaining variation in the dependent variables can be explained by other variables not included in the model, such as the change in bank stock returns, internet infrastructure, and other factors. This shows that the model cannot explain the entire variation of the dependent variables and that there are influences from other factors outside the model's scope. Therefore, we posit that the findings are suitable with the context of the relationship between information search and the app ratings of Vietcombank and that the influence of the independent variables is estimated to be statistically significant in the model.

Table 7. OLS estimation results

Variable	$Ratings^{Stars}$		$Ratings^{Stars}$		$Ratings^{Stars}$		$Google^{VCB}$	
	Coef.	t-statistic	Coef.	t-statistic	Coef.	t-statistic	Coef.	t-statistic
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cons.	-.526853	-0.53	.80409	1.59	1.23237	0.92	2.56065***	17.96
$Google^{Vietcombank}$	.65149***	3.13			.41206	1.66		
$Google_{t-1}^{Vietcombank}$	-.20920	-1.00			-.21034	-0.79		
$Google_{t-2}^{Vietcombank}$					-.18269	-0.70		
$Google_{t-3}^{Vietcombank}$					-.21909	-0.92		
$Google^{VCB}$			.32360***	3.24	.26412**	2.22		
$Google_{t-1}^{VCB}$			.21260**	2.09	.27417**	2.30		
$Google_{t-2}^{VCB}$			-.12562	-1.23	-.03612	-0.31		
$Google_{t-3}^{VCB}$			-.22766**	-2.28	-.17136	-1.52		
$Ratings^{Stars}$							.42639***	4.71
$Ratings_{t-1}^{Stars}$							-.47373***	-4.99
$Ratings_{t-2}^{Stars}$							.21215**	2.28
$Ratings_{t-3}^{Stars}$							-.078024	-0.89
N	124		122		122		122	
R-square	0.0750		0.1213		0.1627		0.2273	
Statistic	4.90***		4.04***		2.75***		8.60***	
Optimal lags	1		3		3		3	

*Note: *, **, and *** are the significant level at 10%, 5%, and 1%, respectively*

Model 4: $Ratings_t^{Stars} = \propto + \sum_{j=0}^{1} \beta_j Google_{t-j}^{Vietcombank} + \mu_t$

Model 5: $Ratings_t^{Stars} = \propto + \sum_{j=0}^{3} \gamma_j Google_{t-j}^{VCB} + \mu_t$

Model 6: $Ratings_t^{Stars} = \propto + \sum_{j=0}^{3} \delta_j Google_{t-j}^{Vietcombank} + \sum_{j=0}^{3} \theta_j Google_{t-j}^{VCB} + \mu_t$

Model 7: $Google_t^{VCB} = \propto + \sum_{j=0}^{3} \delta_j Ratings_{t-j}^{Stars} + \mu_t$

Source: The authors

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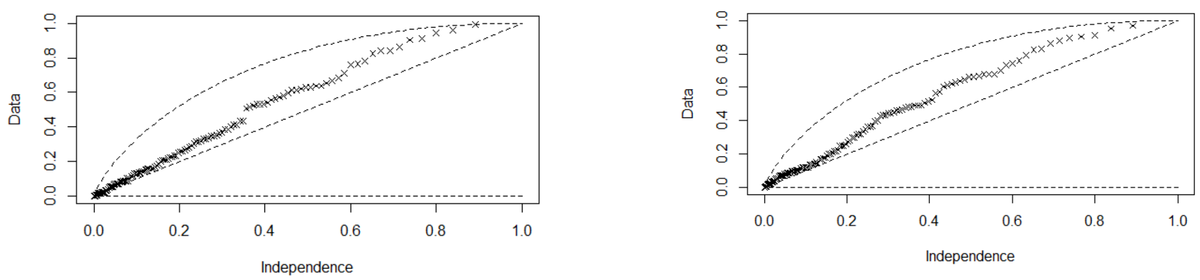
Furthermore, we observed significant coefficients for the Google search variable, indicating its significant effect on the app ratings of Vietcombank. Specifically, we found positive effects for $Google^{Vietcombank}$, $Google^{VCB}$, and $Google_{t-1}^{VCB}$, and a negative effect for $Google_{t-3}^{VCB}$. Additionally, we discovered a significant effect of the app ratings on the search volume of the term "VCB" based on the coefficients of the app ratings variable: Positive effects for $Ratings^{Stars}$ and $Ratings_{t-2}^{Stars}$, and negative effect for $Ratings_{t-1}^{Stars}$.

Copula estimation

The copula approach was employed to assess the relationship between information search and app ratings of Vietcombank in terms of their dependency structure, thereby enhancing our empirical study and strengthening the previous test. Copula serves as an effective tool for modeling multivariate uniform distributions and enables the examination of dependency structures between variables. It is also useful for testing spurious correlations observed in the data. Following the methodologies of Nasir et al. (2019) and Pham et al. (2021), we utilized Kendall plots and non-parametric copula methods to estimate the dependency structure between variables based on their joint marginal distribution. By using these techniques, we addressed the shortcomings of scalar measurements such as correlation and linearity estimation. The application of these techniques enhances the integrity of the experimental study and provides support for the findings of earlier estimations.



Between $Ratings^{Stars}$ and $Google^{Vietcombank}$ *Between $Ratings^{Stars}$ and $Google^{VCB}$*

Figure 4. Kendall-plot graphics

Source: The authors

The Kendall-plot plot illustrates the reciprocal relationship between two variables and uses defined points to identify structural dependence. It is claimed that a pair of variables has structural dependence if the specified points do not lie on the 45-degree line, i.e., if there is no symmetry. Figure 4 shows that pair variables between $Ratings^{Stars}$ and $Google^{Vietcombank}$ and $Ratings^{Stars}$ and $Google^{VCB}$ are dignosed to have a structural dependency.

According to Nasir et al. (2019) and Pham et al. (2021), the Kendall plot provides a graphical diagnosis but not specific information about the structural dependency between variables. Therefore, additional methods such as Gumbel, Clayton, and normal, are considered to enhance the diagnosis of the structural dependence between variables. The estimation result of the Gumbel copula provides parameters to evaluate the upper tail (or right tail) dependency structure in the case of pair variables simultaneously experiencing a positive change. On the other hand, the estimation result of the Clayton copula is used to determine the lower tail (or left tail) dependency structure in the case of pair variables simultaneously experiencing a negative change. The estimation result of the normal copula indicates no tail structural dependency between variables.

In this study, similar to Huynh et al. (2020), the maximum pseudo-likelihood approach was employed to estimate the parameters of the three families of copula. The highest log-likelihood value was considered to determine the best-fit estimation result among the three families of copula.

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Table 8. Estimated parameter results by the three copula approaches

		$\text{Ratings}^{\text{Stars}}$ and $\text{Google}^{\text{Vietcombank}}$	$\text{Ratings}^{\text{Stars}}$ and $\text{Google}^{\text{VCB}}$
Clayton	Parameter	0.4533	0.488
	Loglikelihood	1.024	1.665
Gumbel	Parameter	1.231*	1.243
	Loglikelihood	5.760	6.044
Normal	Parameter	0.289	0.3041*
	Loglikelihood	4.823	5.376

*Note: * is the fittest estimation*

Source: The authors

Table 8 demonstrates that the relationship between $\text{Ratings}^{\text{Stars}}$ and $\text{Google}^{\text{Vietcombank}}$ has been shown to have the strongest upper-tail structural dependency. This analysis shows that there is a strong possibility of simultaneous growth in $\text{Google}^{\text{Vietcombank}}$ and $\text{Ratings}^{\text{Stars}}$. However, it was determined that there was no tail reliance in the link between $\text{Ratings}^{\text{Stars}}$ and $\text{Google}^{\text{VCB}}$. This shows that the simultaneous changes in both variables, whether they rise or fall, are equal.

5. CONCLUSION

Observations of internet users' behaviors in searching for and utilizing mobile apps led the study to choose Vietcombank, a prominent commercial bank in Vietnam, to develop digital banking. Our goal was to investigate how these parameters related to one another. To do this, we gathered time series data on the volume of searches for phrases relating to Vietcombank and the evaluations of the bank's mobile banking app. Then, we used a variety of techniques to examine the link between these series.

In the specific instance of Vietcombank, the estimation results allowed us to ascertain the connection between information search and app ratings. We specifically discovered the following:

- There is a unidirectional causality relationship from the number of searches for "Vietcombank" and the app's ratings.
- The Vietcombank app's ratings and searches for the term "VCB" are determined as bidirectional causality relationship.
- There is a positive impact of search volume on the app ratings.
- There is an upper tail dependency between the search volume of the term "Vietcombank" and the app ratings.
- There is no tail structural dependence structure between the search volume of the term "VCB" and the app ratings.

In conclusion, our findings suggest that the search volume of specific terms related to Vietcombank has a significant impact on the ratings of their mobile banking app, indicating the importance of search behavior in influencing user perceptions and app ratings.

The study has several limitations that point toward directions for further research. Firstly, the empirical evidence presented in the study is based on a case study of Vietcombank, which could introduce bias in the relationship between information search and app ratings. To address this, future research should broaden the data scope by including panel data from multiple banks and regions, such as Southeast Asia and Asia. Additionally, ratings and reviews from the App Store (specifically those running on iOS devices from Apple) should be considered to enhance the breadth of data collection further. Secondly, alternative time series quantitative techniques like ARCH and GARCH should be considered for data analysis. The application of these methods may provide additional estimation results that could lead to exciting findings regarding the relationship between information search and app ratings. Thirdly, it is important to acknowledge that product experience behavior cannot be solely measured by rating stars. Conducting sentiment analysis through text mining of reviews can offer valuable insights. Exploring this direction in further research would be intriguing.

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