Exploring the Impact of the COVID-19 Pandemic on Automobile Sales: A Confirmatory Composite Analysis Using Google Trends Data to Develop a Structural Equation Model

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Received: *February 23, 2023* ***Revised:*** *June 14, 2023* ***Accepted:*** *November 3, 2023*

Abstract

Confirmatory factor analysis (CFA) analyzes latent variables in structural equation models representing unmeasurable attitudes or behaviors. In contrast, confirmatory composite analysis (CCA) uses emergent variables such as capacities, values, and indices. When significant secondary and Google trend data are used, CCA may be preferred over CFA. This study employs CCA and partial least squares to develop a structural equation model. It examines COVID-19's impact on vehicle sales in Thailand. The study uses data from March 2020 to September 2021, including COVID-19 infection rates, newly registered cars, and Google Trends data on COVID-19 and vehicle sales. The results indicate that the overall model fit, and measurement model parameters are outstanding. This suggests a significant negative influence of the COVID-19 pandemic on car sales in Thailand.

The study concluded that CCA and partial least squares were used to analyze the impact of COVID -19 on vehicle sales in Thailand. Analysis of secondary data and Google trend data revealed a significant negative impact of the pandemic on car sales, indicating a negative impact on the automotive industry in Thailand during the indicated period.

Keywords: Confirmatory composite analysis, Google trends, COVID-19, Vehicle sale

Introduction

The COVID-19 pandemic has profoundly impacted on the global economy, with the automobile industry not spared. On December 31, 2019, Wuhan City, China, reported pneumonia cases of an unknown cause to the World Health Organization (WHO). This was later identified as COVID-19 on February 11, 2020, and declared a pandemic on March 11, 2020 (Cucinotta & Vanelli, 2020). Lockdowns implemented in highly infected regions have caused significant disruption to global auto sales (Pharmaceutical Technology, 2021). In Thailand, famed for its car manufacturing industry, there have been three outbreaks of the virus , stringent measures imposed in sensitive areas, and increased vaccination rates in high-risk areas, all of which have degraded business activity in the car sector (Thailand Board of Investment, 2017). The far-reaching implications of COVID-19 on the worldwide utomobile industry are of great concern, particularly for Thailand's economy.

Many publications recently released studies on COVID-19 (Nguyen et al., 2020; Prasanth et al., 2021) that utilized Google Trends, to predict the current or near future state more quickly and efficiently than official data (Choi & Varian, 2009). Should the correlation of the dependent variables with Google Trends be insignificant, one should average out the correlations of multiple broad searching queries (Nguyen et al., 2020). Google Trends estimates car sales, unemployment, tourist demands, stock markets, and crypto markets. All these endeavors involve time series econometrics and thus demand stationary data (Granger & Newbold, 1974). Choi and Variance (2009) conducted research that utilized simple autoregression (AR), bypassing the need for stationary data pre-processing but which might lead to spurious regression when one or more parameters are large and significant. This study used CCA to examine the relationship between the COVID-19 pandemic and automobile sales. The use of CCA in this study is entirely appropriate, as it considers all relevant indicators, including the number of COVID-19 cases and Google searches related to the virus, to generate an emergent variable. Car sales were determined by analyzing registered vehicles and Google search trend data. These four observable variables were transformed into emergent variables suitable for CCA. The study aimed to investigate the impact of the COVID-19 pandemic on car sales. This is the first time CCA has been applied to address this research gap.

When latent variables reflecting unmeasurable attitudes or behaviors are included, most structural equation models can use CFA for analysis. According to Henseler et al. (2014), CCA is a technique that uses artifact or emergent variables such as capacities, values, and indices. In addition, Yu et al. (2021), Jhantasana (2023) indicate that emergent variables can be formed from latent variables and observable variables. This study prefers CCA over CFA because secondary data and Google trend data are more comprehensive and better suited for CCA.

In this study, a structural equation model with CCA was developed to analyze the impact of COVID-19 on vehicle sales. Based on the theory of Henseler and Schuberth (2020) and using Google Trends and secondary data, this research will contribute to both theory and practice by providing insights into the impact of COVID-19 on vehicle sales. This, in turn, will enable companies to plan, develop, and optimize strategies for vehicle sales.

Literature review

Car sales and cars registered in Thailand

The COVID-19 pandemic has had a significant impact on the global automotive industry, with various studies focusing on the effects of the pandemic on different aspects of the industry. For instance, Leenawong and Chaikajonwat (2022) highlight the challenges traditional forecasting methods face in predicting car sales during the pandemic period in Thailand. This led to the proposal of a modified Holt forecasting method incorporating seasonality and event components. This proved effective in predicting car sales. Similarly, Shevchenko, et al. (2021) examine the impact of the pandemic on the global automotive industry, specifically on car production and sales, by analyzing changes in production and sales volume by country. The study provides insight into the pandemic's impact on the industry, classifying countries based on the pandemic's destructive effects and identifying ways to overcome negative consequences (Shevchenko et al., 2021).

Furthermore, Lyu (2022) evaluates the impact of COVID-19 on the Chinese automotive industry, revealing that Chinese car sales were significantly affected, with higher-priced car models being impacted less and Chinese models being impacted more. Kufelová and Raková (2020) focus on the economic impacts of the pandemic on the Slovak economy, specifically on the automotive industry, leading to production shutdowns and supply chain disruptions. Török (2020) examines the adverse effects of the pandemic on the upcoming car market in the European Union in the first half of 2020. It highlights the high dependence of the Union economy on automobile emissions. The study emphasizes the potential for crises to fundamentally change consumer behaviour and the need for the automobile sector to be prepared for these changes.

Additionally, Lopez and Gil-Alana (2023) investigate the persistence of vehicle sales in the US during the pandemic, finding that shocks are transitory with a faster recovery over time, indicating industry's strength. These studies collectively demonstrate the far-reaching effects of the COVID-19 pandemic on the global automotive industry, with various countries and markets experiencing different levels of impact. The findings suggest that the industry needs to be prepared for changes in consumer behaviour and supply chain disruptions as crises emerge.

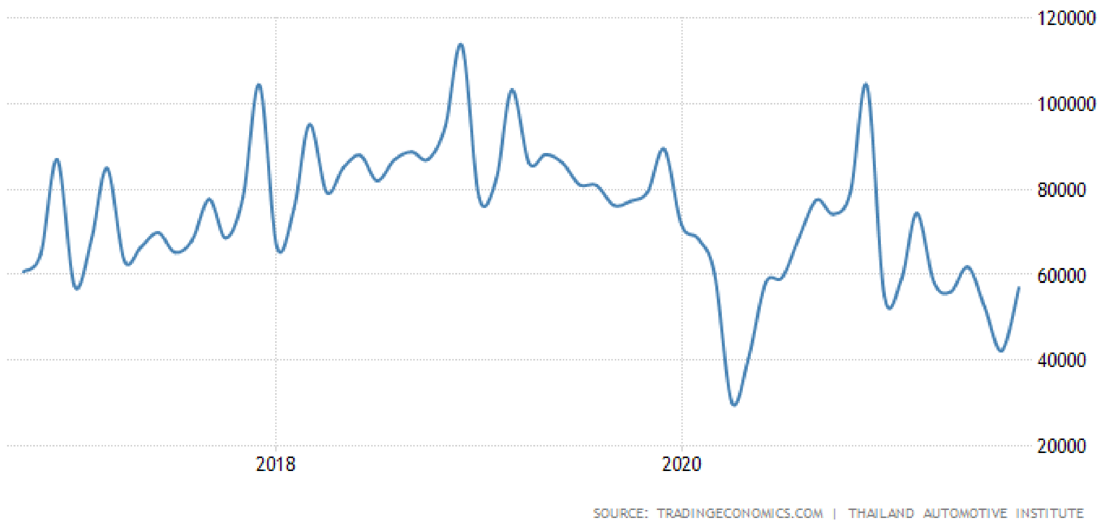

Figure 1 Car sales during five-years
Source: https://tradingeconomics.com/thailand/total-vehicle-sales

According to the Thailand Automotive Institute, a significant year-on-year decrease of 38.75% in August 2021's automotive sales, with only 42,176 units sold compared to the previous year's figure of 68,883. Figure 1, which shows data from 2017 to mid-year 2021, also reflects the impact of the first wave of COVID-19 in Thailand, with a notable drop in car sales from March to April 2020 (Leenawong & Chaikajonwat, 2022). While the pandemic certainly contributed to this decline, other factors, such as a shortage of microprocessor chips were also at play. This added further strain to an already struggling industry. This chip shortage was caused by various factors, including the pandemic and a fire at a chip manufacturing plant in Japan (Kasikorn Research Center, 2021a). As a result, domestic vehicle sales in Thailand were approximately 9% lower than the previous year's figures.

The Department of Land Transportation collects registration data for all types of vehicles, with four categories accounting for more than 95% of registered automobiles. These include sedans with no more than 7 seats (type 1), microbus and passenger vans with more than 7 seats (type 2), vans/pickups (type 3) and motorbikes (type 12). The research presented in this paper focuses on automobile sales, capturing car registration data from types 1, 2, and 3 during the COVID-19 pandemic period between March 2020 and September 2021. Table 1 shows the total number of cars sold during this period. It registers between 30,000 to 62,000, 1,000 to 3,000, and 15,000 to 23,000 vehicles per month for type 1, type 2, and type 3 vehicles, respectively. Initially, the reported infections in March had no impact on car sales. However, it decreased in April as the second wave started in December 2020. This led to an increase in infections in January 2021, causing a double jump in automobile sales compared to December. The third wave that began in April caused registrations to drop significantly. Notably, the highest reported infection levels were seen in August, while July had the least car registrations.

Table 1 Registered cars (type 1, 2 and 3)

Month	2020	2021
January	-	83,785
February	-	69,799
March	83,161	80,085
April	59,830	61,214
May	48,659	70,565
June	54,313	64,059
July	54,171	46,640
August	61,999	56,817
September	62,873	53,411
October	62,993	-
November	62,458	-
December	48,466	-

Source: Department of land transport (2021)

Coronavirus disease

In March 2020, Thailand reported 1,651 COVID-19 cases, and as a result, some countries experienced an economic downturn. This affected 4.7 million people and significantly impacted their ability to purchase goods such as cars. During the initial wave of the pandemic, approximately 3-4 thousand people contracted the virus in the first month. The second wave began in December 2020, escalating from 7 thousand infections to 19 thousand in January 2021 and around 30 thousand in March 2021. Nonetheless, the third wave has been more severe - starting with 65,000 cases in April, it peaked at 600 thousand infected people in August before beginning a descent.

Table 2 Number of COVID-19 infectious people from March 2020 to September 2021

Month	2020	2021
January	0	19,618
February	0	25,951
March	1,651	28,863
April	2,954	65,153
May	3,081	159,792
June	3,171	254,515
July	3,310	337,986
August	3,412	608,069
September	3,569	399,696
October	3,784	-
November	4,008	-
December	7,163	-
Total	**36,103**	**1,899,643**

Source: COVID-Department disease control[1], 2021

Google Trends data

Google Trends is an effective tool for uncovering search terms and topics among a specific audience. It allows users to narrow their results by region, category, time, or search type. You can deternine what people intend to do with the data (Chamberlin, 2010). Choi and Varian (2009) used it to forecast car sales and unemployment. Google (2021) offers anonymized and aggregated samples of actual search requests without personally identifying information. Google Trends includes real-time data from a seven-day sample, or non-real-time data, beginning in 2004 and up to 36 hours beforehand. Normalizing search query data

[1] https://ddc.moph.go.th/viralpneumonia/situation_more.php

according to time and location makes it possible to compare words regardless of when and where the query was made.

1. Each data point is divided by the number of searches for the location and time it covers to determine its relative popularity. Otherwise, the places with the most searches always appear first.

2. Based on the percentage of searches on a topic compared to all searches on all topics, the obtained values are scaled on a 0 to 100 scale.

3. Different areas with the same level of interest may have different overall search volumes.

Google Trends data may be downloaded as an a. csv file by selecting the symbol "⬇" which appears to the right and above the line graph. This research used five automotive search terms: "โตโยต้า" "ฮอนด้า" "บริษัทอีซูซุมอเตอร์" "นิสสัน" and "มาสด้า," which correspond to Toyota, Honda, Isuzu motor company, Nissan, and Mazda, respectively. The results are shown in Figure 2. Figure 3 displays three the search terms in This: "โควิด," "โรคติดเชื้อไวรัสโคโรนา 2019," and "ฉีดวัคซีน" which stand for "COVID," "Coronavirus disease 2019," and "vaccination," respectively.

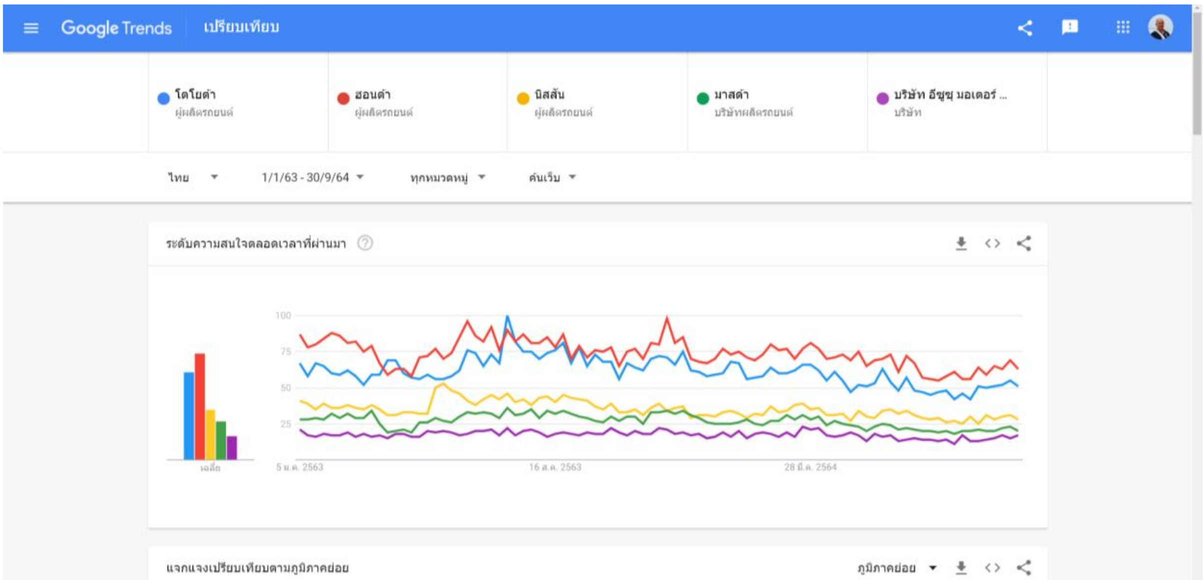

Figure 2 Line graph of five queries on cars
source: Google Trends (2021)

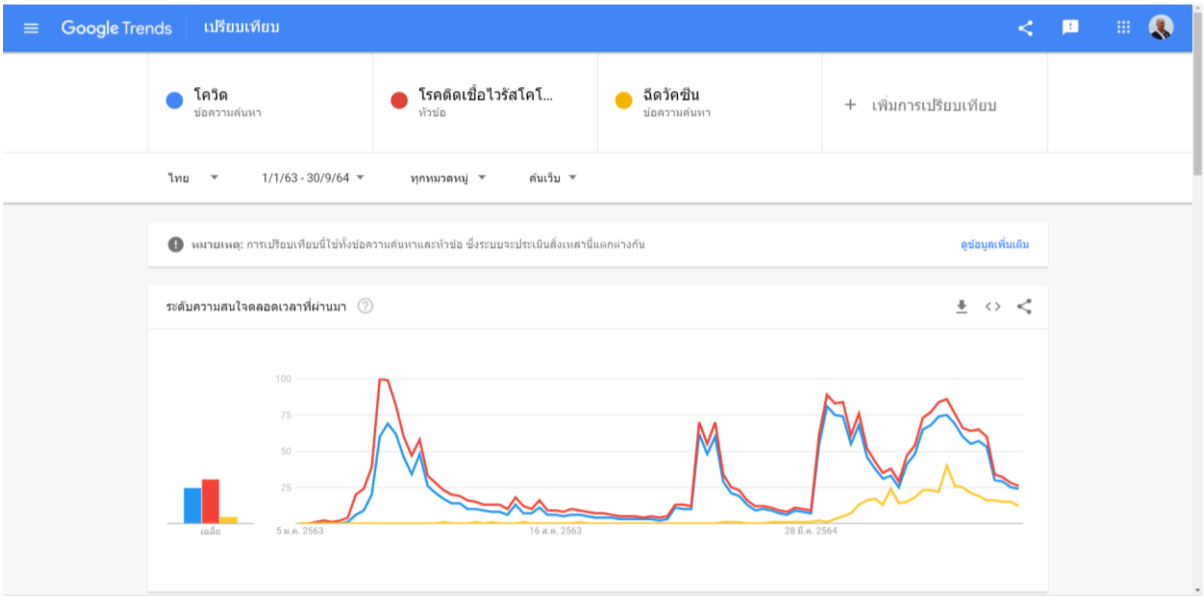

Figure 3 Line graph of three queries on COVID-19
Source: Google Trend (2021)

Choi and Varian (2009) pioneered the Google Trends application in economic forecasting. Since then, this tool has been widely used, including in epidemiology (Cervellin et al., 2017; Mavragani & Ochoa, 2019), labor market forecasting (Nakavachara & Lekfuangfu, 2018), predicting car sales (Choi & Varian, 2012; Collison, 2020; Nymand-Andersen & Pantelidis, 2018), unemployment (Barreira et al., 2013; Kundu & Singhania, 2020; Mulero & García-Hiernaux, 2021), tourism (Yang et al. 2021), stock prices (Aziz & Ansari 2021; Yoshinaga & Rocco 2020) and cryptocurrency markets (Nasir et al. 2019). Additionally, Brodeur et al. (2020) demonstrated how Google Trends could be used in researching COVID-19 impacts on mental health. Their studies, they discovered that feelings such as loneliness and anxiety were more pronounced when governments-imposed lockdown measures and people researched terms such as stress, suicide, and divorce. Prasanth et al. (2021) collected their data using the average of nine search terms' correlations, while Nguyen et al. (2020) collected data using 13 search words.

Conceptual framework and assumption

The conceptual framework for studying COVID-19's influence on automobile sales, in which all indicators are emergent variables or composite models, is ideal for confirmatory composite analysis. The first indicator is the number of cars registered with the Department of Land Transport, representing automobile sales. The second indicator is the number of COVID-19 pandemic reports received by the Centre for COVID-19 Situation Administration (CCSA). The third and fourth indicators are Google Trends searches for COVID-19 and automobiles, respectively. The following hypothesis:

H1: The number of COVID-19 infectious people is inversely proportional to the number of automobiles sold.

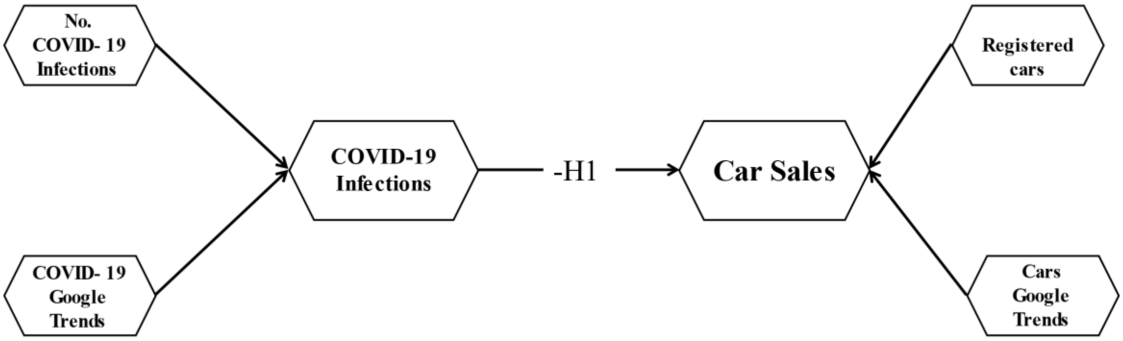

Figure 4 Conceptual framework and hypothesis

Research methodology

Data

The data set consists of four indicators, two from secondary sources and two from Google Trends. The Department of Land Transportation and the CCSA provided secondary data. Google Trends data were created by correlating search words and establishing an average of relevant search terms. In the search for automobiles, five search terms were used: "โตโยต้า" "ฮอนด้า" "บริษัทอีซูซุมอเตอร์" "นิสสัน" and "มาสด้า." Using Google Trends, the COVID-19 search used three terms: "โควิด" "โรคติดเชื้อไวรัสโคโรนา 2019" and "ฉีดวัคซีน". The appropriate search terms had correlations equal to or greater than 0.7. Thus, the most relevant search terms for vehicles were "โตโยต้า" "ฮอนด้า" "นิสสัน" and "มาสด้า," which were then used to produce the data by averaging the Google data for the four search terms. Google Trends data for the COVID-19 pandemic used two search terms. Additionally, Google Trends provided weekly data, which had to be converted to monthly data. The correlation coefficients were calculated as follows.

$$corr(X,Y) = \frac{\sum_{i=1}^{T}(x_i - \bar{x}) * (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{T}(x_i - \bar{x})^2} * \sqrt{\sum_{i=1}^{T}(y_i - \bar{y})^2}} \quad (1)$$

Table 3 The correlations of the search terms

Automobile			Corona virus disease 2019		
Search term	**Correlation**	**P-value**	**Search term**	**Correlation**	**P-value**
โตโยต้า (Toyota)	0.809	0.000	โควิด (COVID)	1	0.000
ฮอนด้า (Honda)	1	0.000	โรคติดเชื้อไวรัสโคโรนา 2019 (Corona virus disease 2019)	0.999	0.000
บริษัทอีซูซุมอเตอร์ (Isuzu Motor Company)	0.622	0.000	ฉีดวัคซีน (Vaccinate)	0.492	0.001
นิสสัน (Nissan)	0.717	0.000	-	-	-
มาสด้า (Mazda)	0.805	0.000	-	-	-

Source: Calculations

Confirmatory composite analysis

The four variables were connected to the indicator, indicating that they were emergent variables that needed a composite model. Henseler (2017b) uses confirmatory composite analysis when all variables in the model are emergent. There are four steps: model specification, identification, estimation, and assessment. All are involved in confirmatory factor analysis (Schuberth, 2021). However, the researcher may achieve the results obtained in step four using ADANCO. Thus, to ensure the quality of the CCA, the researcher must conduct a comprehensive investigation in step 1. Further, there are other types of CCAs developed by Hair et al. (2020). It is not based on confirmatory theoretical principles as Hubona et al. (2021) propose named PLS_CCA. They may be used to investigate the differences between CCA and PLS-CCA, as described in Hubona et al. (2021) and Henseler and Schuberth (2020). This research is based on Henseler's (2017b) CCA, which requires the investigation of three sub-models: model fit, measurement model, and structural model.

The model fit tests employ bootstrapping to determine the chance of a substantial correlation matrix discrepancy if the hypothesized model is accurate (Henseler, 2017a). Three parameters must be considered while fitting the model: the standard root mean squared residual (SRMR), the geodesic discrepancy (d_G), and the unweighted least squares discrepancy (d_{ULS}). The SRMR d_{ULS} and d_G parameters measure the difference between empirical and model-implied correlation matrices. The lower the SRMR, d_{ULS}, and d_G values, the more closely the model approximates the theoretical model. If the theoretical model is valid, the SRMR will be bootstrap-based at 95 percent (HI95) and 99 percentiles (HI99) if the theoretical model is valid. If the first requirement is implausible, then the SRMR must be less than 0.08 (Hu & Bentler, 1999), which indicates an appropriate model fit quality.

Henseler (2017c) argues that three factors should be examined when evaluating the quality of a CCA measurement model: nomological validity, reliability, and weights (composition). The model fit tests for the saturated model establish the external validity or measurement model for composites that do not exist in the factor model (Henseler et al., 2016).

Model fit may enhance nomological validity by assessing and correlating estimated weights, their sign, and size to a researcher's theory. If the weight estimates are multicollinear, the researcher should investigate the correlation patterns between the observable variables that comprise the emergent variables (Schuberth, 2021). Remove multicollinearity indicators with a VIF (variance inflation factor) of more than 5 to improve model fit, Preferably, they should all be less than 3. Hair et al. (2019) found that loading higher than 0.5 is required when weight is insignificant with t statistics less than 1.96. The composite's reliability may be assessed against its nomological validity to determine reliability. When a composite is evaluated using precise and observable variables, no random measurement error occurs, and its reliability is one (Henseler, 2017c). If The composite will only be reliable if the indicators contain random measurement errors (see Henseler, 2017c).

The significance of the path coefficient, the effect size (f^2), and the coefficient of determination (R^2) are all elements of structural model quality. A path coefficient quantifies the direct impact of an independent variable on a dependent variable. Its significance is indicated by a t-statistic value of 1.96 or more. Effect size quantifies a direct effect. Its value might be more or equal to zero. Cohen (1988) defined the effect size as 0.02, 0.15, and 0.35 for weak, moderate, and vigorous, respectively, with a significant effect size considered to be above 0.15. In the presence of an endogenous variable with a value between 0 and 1, the coefficient of determination measures the amount of variance explained by the independent variables. It is sometimes called in-sample predictive power (Rigdon, 2012), and serves as a proxy for a model's explanatory power (Shmueli & Koppius, 2011). The standard for the determinant coefficients is 0.25, 0.50, and 0.75, which correspond to weak, moderate, and substantial, respectively (Henseler et al., 2009; Hair et al., 2011), implying that coefficients of moderate and above are acceptable.

Research finding

Total model fit

Table 4 shows the total model fit, suggesting that empirical data and model-implied correlation matrices are equivalent. The SRMR d_{ULS} and d_G values are smaller than the 95 percent bootstrapping test. Additionally, the results imply a high degree of nomological validity.

Table 4 Total model fit indexes

Parameters	**Value**	**HI95**	**HI99**
SRMR	0.028	0.081	0.119
d_{ULS}	0.008	0.065	0.141
d_G	0.005	0.045	0.096

Source: Calculations

Measurement model

According to Henseler et al. (2016), model fit tests on a saturated model may show measurement validity, implying nomological validity. The weight sizes and signs are significant and consistent with the t statistics for weights larger than 1.96, most notably Google Trends data for vehicle-related searches. The VIFs show ideal multicollinearity being less than 3. Inner models are superior.

Table 5 Parameter of the measurement model

Indicators	Loading	Weight	t statistics of weight	VIF
CARs Registered	0.262	0.221	2.227	1.002
CAR_GT	0.975	0.966	18.078	1.002
COVID-19	0.911	0.546	3.161	1.778
COVID_GT	0.912	0.551	3.435	1.778

Source: Calculation

Structural model

Table 6 and Figure 5 criteria used for evaluating the quality of a structural model that statistically exhibits an outstanding degree of quality. Additionally, the t-value, f^2, and R^2 values are significant, indicating a negative correlation between the COVID-19 pandemic and vehicle sales.

Table 6 Parameters of a structural model

Effect	Beta	t-value	p-value	Cohen's f^2	R^2	Hypothesis
COVID -> Car sale	-0.910	16.528	0.000	4.839	0.829	Accepted

Source: Calculations

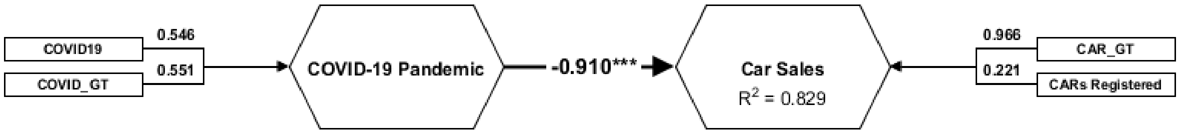

Figure 5 Parameter of the structural model

Where:
COVID-19 is the number of infection cases of COVID-19
COVID_GT is Google Trends data for searches related to COVID-19
CARs Registered concern vehicles registered as type 1. 2, and 3
CAR_GT is Google Trends data for searches related to cars.

Discussion and summary of research

Discussion

The article suggests that COVID-19 has had a strongly negative impact on automotive sales. The pandemic has caused economic havoc worldwide, with Thailand experiencing declining revenue across several sectors and facing job losses for millions of people. These factors have indirectly affected people's ability to buy cars, as noted by the Kasikorn Research Center (2021b), which reports that COVID-19 has affected automotive manufacturing and sales. While Google Trends can be an effective tool for researching topics such as the pandemic and consumer behavior, it is critical to note that the platform only approximates vehicle sales statistics, as confirmed by Brodeur et al. (2020). Nevertheless, research by Lekfuangfu and Suwanprasert (2020) highlights the potential of Google Trends in revealing real-time trends and forecasting economic situations. Indeed, policymakers and businesses can use Google Trends in conjunction with official data to gain insights into consumer behavior over time, as previously noted by Choi and Variance (2012) and relied upon by Thailand's government for economic indicators (Bank of Thailand, 2020; Fiscal Policy Office, 2020).

Studies by Lopez and Gil-Alana (2023) and Leenawong and haikajonwat (2022) provide further insights into COVID-19's impact on the automotive industry. Lopez and Gil-Alana's study of US automobile sales finds that the industry is evolving towards electric and intelligent cars, and that shocks have long-lasting effects. Meanwhile, Leenawong & Chaikajonwat's research in Thailand identifies the need to modify forecasting methods to better predict car sales data during the pandemic. Shevchenko, et al (2021) study of the global automotive industry provide a practical framework for classifying countries based on the degree of adverse effects of COVID-19 on car production and sales. The authors suggest that this framework can help identify ways to overcome the pandemic's negative impacts on the industry.

Other studies, such as those by Lyu (2022); Kufelová and Raková (2020); Török (2020) also shed light on the effects of COVID-19 on the automotive industry, particularly in China and Europe. Török emphasizes the importance of stimulating market demand with public funds to counteract the decline in new car sales and the resulting panic in the automotive value chain. Ultimately, sales data remains crucial for assessing product success and customer demand, as well as informing future market movements, and benefitting investors (Lopez & Gil-Alana, 2023).

Theoretical contribution & managerial implication

This study's theoretical contribution is the importance of considering emergent variables in understanding complex phenomena. The study highlights that emergent variables connected to value, competence, and index can predict attitudes and behaviors. This finding is consistent with previous WHO research, highlighting the relevance of emergent variables in understanding complex phenomena (Hubona et al., 2021).

From a managerial perspective, the study's findings offer valuable insights for policymakers and businesses in forecasting and planning for future economic conditions. The practical value of using Google Trends data in combination with official data for analyzing consumer behavior over time is highlighted. This is particularly relevant in the context of the COVID-19 pandemic, as it offers a more complete picture of the impact of the pandemic on consumer behavior (Choi & Varian, 2012; Lekfuangfu & Suwanprasert, 2020). The study suggests that policymakers and businesses can use Google Trends data in combination with official data to analyze consumer behavior over time. This can help forecast and plan future economic conditions. Additionally, the study emphasizes the importance of considering emergent variables in decision-making processes, particularly in understanding consumer attitudes and behaviors (Hubona et al., 2021).

Limitations and Directions of Future Research

Limitations

One of the limitations of our study is that the model's simplicity with only two emergent variables may limit the investigation of correlation matrices between empirical and model-implied correlation matrices. Moreover, using only two COVID-19 search terms may limit the reliability of the statistics compared to Google Trends for automobile searches (Dyckhoff et al., 2013; Brodeur et al., 2020).

Directions for Future Research

Researchers employ secondary data and Google Trends to develop time series econometric models and lag variables. However, Google Trends lacks the lag variables for partial least squares structural equation models, particularly confirmatory composite models. Because Google Trends data is updated more often than official data, researchers should typically employ secondary data and Google Trends as time lag variables in future studies. This is to make partial least squares predictions based on PLS-CCA and SmartPLS. Additionally, CCA stands for confirmatory composite analysis using ADANCO (Henseler, 2017a), GSCAPro (Hwang et al., 2021), or the cSEM (Rademaker, 2021) or GESCA packages of the R programming language (Hwang et al., 2017).

Conclusion

The study demonstrates the negative impact of the COVID-19 pandemic on automotive sales in Thailand. Confirmatory composite analysis and partial least squares on Google Trends data is a novel approach. It offers valuable insights into the relationship between COVID-19 and vehicle sales. The findings highlight the importance of emergent variables in predicting consumer attitudes and behaviors. They also highlight the practical value of using Google Trends data in combination with official data for analyzing consumer behavior over time. Moreover, the study emphasizes the importance of considering emergent variables in decision-making processes, particularly in understanding consumer attitudes and behaviors.

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