Journal of the Association for Information Systems

Volume 21
Issue 3 *Special Section: Accumulation and Evolution of Knowledge in Design Science Research (pp. 520-544, 664-810)*

Article 6

5-22-2020

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Recommended Citation

Luo, Peng; Ngai, Eric W. T.; and Tian, Xin (2020) "Exploring the Dynamic Influence of Visit Behavior on Online Store Sales Performance: An Empirical Investigation," *Journal of the Association for Information Systems*, 21(3), .
DOI: 10.17705/1jais.00614
Available at: https://aisel.aisnet.org/jais/vol21/iss3/6

Journal of the Association for Information Systems (2020) **21**(3), 607-636
doi: 10.17705/1jais.00614

RESEARCH ARTICLE

ISSN 1536-9323

Exploring the Dynamic Influence of Visit Behavior on Online Store Sales Performance: An Empirical Investigation

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Abstract

The sales performance of online stores plays a critical role in the economy and has attracted increasing attention from scholars. This study focuses on different aspects of the visit behavior of online consumers and explores the dynamic relationships between visit behavior factors and the sales performance of online stores. We adopt comprehensive visit behavior measures, including number of visitors, repeat visits, visit duration, visitor bookmarking behavior, and visitor attributes, and examine whether these metrics are related to sales performance, what the dynamics of the observed relationships are, and which metric is the most important factor in these relationships. We adopt the vector autoregression model with exogenous variables to investigate the dynamic relationships of visit behavior variables with sales performance. We also assess the relative importance of different metrics in explaining sales performance. The findings reveal that visit behavior measures have a strong relationship with sales performance measures. Among the different metrics, the repeat visit metric has the significantly strongest relationship with sales performance, followed by the number of visitors. This study offers new insights for the visit behavior and sales performance literature as well as novel strategies for managers of online stores.

Keywords: Visit Behavior, Sales Performance, Online Store, Dynamic Influence, E-Commerce

Subhajyoti Bandyopadhyay was the accepting senior editor. This research article was submitted on September 15, 2018 and underwent two revisions.

1 Introduction

Easily accessible, highly efficient, and cost effective, e-commerce has been widely adopted by consumers and retailers and accounts for an important part of the global economy (Richard & Habibi, 2016). Internet advertising has exhibited great power and potential in promoting e-commerce sales. In 2016, an estimated 1.61 billion people worldwide purchased goods online, and global e-tail sales amounted to US$1.9 trillion, with growth predicted to reach US$4.06 trillion by 2020. [1] In the Chinese market, Alibaba's sales exceeded US$9.3 billion in 2014, US$14.3 billion in 2015, and more than US$17.8 billion in 2016. [2] E-commerce has become increasingly important in the global economy and has become a part of daily life worldwide.

Reflecting the importance of e-commerce, scholars have also shown a particularly strong interest in e-commerce factors that affect online sales performance. Unlike the existing e-commerce sales performance studies that focus on factors such as word-of-mouth (Kuan et al., 2015; Lin & Wang, 2018), marketing

[1] https://www.statista.com/ topics/871/online-shopping/).

[2] http://www.bbc.com/news/37946470

strategies (Luo et al., 2016; Queiroz, 2017) and product characteristics (Lang et al., 2015; Lee et al., 2015), in this paper we consider another important perspective—visit behavior—given that online sales are generated by online visitors. The primary research stream in the existing visit behavior literature discusses the use of model development to simulate the online visit process and examine potential impacts of visitor number (Rishika et al., 2013), repeat visits (Moe & Fader, 2004a), and visit duration (Mallapragada et al., 2016). In terms of the empirical studies on visit behavior, several scholars have adopted the survey method to collect data from consumers and explore the relationship between visit behavior and dependent variables such as trust (Wu et al., 2010), satisfaction (Polites et al., 2012), and purchase intention (Lin, 2007). Other empirical studies obtain real website traffic data, but these studies generally focus on limited aspects of visit behavior, such as the relationships between visit duration and conversion rate (Lin et al., 2010), the relationship between visit frequency and profitability (Rishika et al., 2013), and the impact of page views and visit duration on sales performance (Mallapragada et al., 2016). However, in terms of secondary data from web traffic in online stores, researchers rarely use a single model to investigate the dynamic impacts of these measures of visit behavior on sales performance. Therefore, the importance of different visit behavior variables remains unknown.

We enter this discourse by constructing a complex and comprehensive research model that includes different aspects of visit behavior. In the existing literature, scholars investigate the different measurements of visit behavior separately and focus on the strong influence of visitor number (Rishika et al., 2013), repeat visits (Moe & Fader, 2004a), visit duration (Mallapragada et al., 2016), and visitor attributes (Danaher et al., 2006) on sales performance in online stores. These factors measuring visit behavior have correlations with each other and some factors of visit behavior also have the potential to invoke other visit behavior factors. Taking visitor attribute (i.e., regular or new visitor) as an example, we assume that regular visitors visit online stores repeatedly and spend a longer time in online stores than do new visitors. Thus, if an online store has many regular customers on a specific day, the data may reflect a higher number of repeat visits and longer visit duration for that day. However, the general focus of existing research on one or two aspects of visit behavior is potentially problematic because significant influential factors may be ignored. Thus, we question whether different measures of visit behavior would also exert a strong influence on sales performance if a variety of different visit behavior metrics and other potential factors were included in a single model. Moreover, the previous empirical research mainly focuses on the static relationship between visit behavior and sales performance by using a simple regression model or structural equation model (Lin et al., 2010; Roy et al., 2014). However, the dynamic influence of visit behavior remains unknown, and understanding this influence is essential to for making accurate theoretical and practical contributions. For example, it may be important to determine whether an increase in the number of visitors on one day has an influence on the sales performance of online stores on the following day or days. This information could help store managers predict sales performance and evaluate and design appropriate marketing strategies. Thus, we pose the following research question: *How do measures of visit behavior, such as number of visitors, repeat visits, visit duration, visitor bookmarking behavior, and visitor attributes, dynamically affect sales performance when evaluated within a single model?*

By evaluating the different perspectives of visit behavior within a single model, we seek to identify the true impacts of different measures of visit behavior on sales performance, which would then allow us to examine the relative importance of different factors of visit behavior and determine which is most important for sales performance. Regarding practical implications, knowing which factors play a crucial role in sales performance is useful. For example, assuming that visit duration is more important than visitor number for enhancing sales performance, an online store manager who is not aware of this fact may focus simply on increasing investment in advertisement, while a more efficient way of increasing sales would be to focus more on the design of the online store page to motivate customers to spend more time at the online store. If longer visit durations are recognized as correlating with more sales, this may in turn enable managers to invest more efficiently. Thus, our second research question asks: *Which visit behavior factor has the strongest relationship with sales performance?*

To answer these research questions, we first collected data from an online store, specifically from the most important Chinese e-commerce website, Tmall (www.tmall.com), owned by Alibaba Group (www.alibabagroup.com), a platform used by local Chinese and international businesses to sell brand name goods to consumers in mainland China, Hong Kong, Macau, and Taiwan. We obtained online store information, including sales information, consumer visit behavior, and rating information, from the website and then use a vector autoregression with exogenous variables (VARX) model that employs a time-series technique. The model has been widely used to examine dynamic relationships between variables and their cross effects (Luo et al., 2013; Tirunillai & Tellis, 2012). Using the VARX model as our basis, we also tested the effects of different variables on sales performance, explored the impulse response of sales performance to our independent variables, and assessed the relative impact of the dependent variables on store sales performance.

Our research contributes to the existing research in several ways. First, we explore the dynamic effects on sales performance of visit behavior measures including visitor numbers, repeat visits, visit duration, visitor bookmarking behavior, and visitor attributes. This study extends the existing research on the traditional factors and static influences that enhance sales performance. Second, we compare the importance of different factors and test the significance of these comparisons. Our research not only identifies the significant variables but also articulates the critical factors that affect sales performance. Third, this study presents practical suggestions on highly effective ways to improve the sales performance of online stores.

The remainder of the article is organized as follows. Section 2 provides an overview of the related literature regarding online consumer visit behavior. Section 3 introduces data, measures, and our research framework. Section 4 presents the results of empirical tests, robustness tests, and other tests, and the final section concludes by discussing implications for theory and practice.

2 Literature Review of Online Visit Behavior

Our study is related to the research on visit behavior of online consumers. In terms of research methods, previous studies can be categorized into studies based on the use of visit behavior models and those based on empirical relationships.

Visit behavior as measured through modeling has been widely researched in the existing literature. Different measures of visit behavior, such as repeat visits (Bhatnagar et al., 2016), visit duration (Danaher & Smith, 2011), and visitor attributes (Danaher et al., 2006), are significant factors in marketing strategies. Repeat visits, measuring the visitation frequency of visitors, is an important factor that plays a significant role in existing research models in e-commerce (Moe & Fader, 2004a). Visit duration is defined as the amount of time that a user spends on a website; this construct is a crucial factor in existing research models (Montgomery et al., 2004). Based on the multivariate stochastic model, Panagiotelis et al. (2014) examined the nonlinear relationship among visit behavior (visit duration), purchase incidence, and sales performance. Visitor attributes measure the characteristics of visitors, such as age, gender, and whether customers are new or not, and may strongly influence consumers' purchase intentions (Danaher et al., 2006). While some studies have explored the relationship between two or more factors and visit behavior, only a few studies have explored this relationship in a complex model. Bucklin and Sismeiro (2003) developed and estimated a Tobit model of visit behavior and examined two aspects of visit behavior, namely repeat visit and visit duration. By considering cross-sectional variations and changes over time, Moe and Fader (2004b) adopted an individual-level model to study the relationship between visiting frequency and purchasing propensity in e-commerce websites. Danaher et al. (2006) used the random effects model to examine the influence of visitor attributes (demographics), text, and graphic content on visit duration.

In the existing research related to visit behavior, empirical studies are limited. An important part of this research stream focuses on the use of the survey method to obtain data and examine the relationship between a single visit factor and dependent variables, such as satisfaction, trust, and purchase intentions. Polites et al. (2012) studied the relationship between visit duration (stickiness) and consumer satisfaction, Roy et al. (2014) examined the impacts of visit duration (stickiness) on word-of-mouth promotion, Lin (2007) explored the effect of visit duration (stickiness) on purchase intention, and Wu et al. (2010) investigated the influence of visit duration (stickiness) on trust. Other studies also adopted the survey method to collect data and explored the relationship between visit behavior and other factors (Lu & Lee, 2010). For example, Chung et al. (2014) proposed a model that examined the impact of a booth recommender system on unplanned visit behavior using the survey method to collect data.

In terms of real-time website traffic data, Jiang et al. (2013) conducted a simple statistical analysis and used Zipf's law to illustrate Chinese users' visit behavior on websites. Previous studies focused on the single relationship between one specific visit factor and a dependent variable. For example, Lin et al. (2010) collected data with designated client-side monitoring software that recorded each instance of actual visiting behavior; they also examined the relationship between visit stickiness and the conversion rate of an e-tailer. By using data on customers' visit behavior derived from data from social media and individual customer-level transactions, Rishika et al. (2013) showed the strong effect of the customers' social media participation on visit frequency and profitability. Mallapragada et al. (2016) focused on two main visit behavior factors, namely page views and visit duration; they demonstrated the strong impacts of visit behavior on online sales performance. Other scholars also adopted visit behavior as the dependent variable and examined the impacts of various factors, such as shopping experience (Pentina et al., 2011), website design (McCoy et al., 2017), and satisfaction with the virtual community (De Valck et al., 2007).

However, existing studies, especially the empirical works that focus on real-time website traffic, mostly focus on one or two aspects of visit behavior and ignore other measures, such as number of visitors, repeat visits, visit duration, visitor bookmarking behavior, and visitor attributes. Table 1 presents a summary of the literature on visit behavior. The method of identifying unique visitors has been widely examined in computer science (Kneževi & Vidas-Bubanja, 2010), and the number of visitors is regarded as a significant factor in marketing strategy (Sharma & Gupta, 2012). Visitor bookmarking behavior has also been examined as an important factor affecting sales performance (Benz et al., 2007; Wilson & Woodside, 1991). To address the lack of research on multiple aspects of visit behavior evaluated in a single model, we collect data from an e-commerce website and examine different measures of visit behavior and sales performance. Our empirical study measures the impacts of different visit behavior measures, such as number of visitors, repeat visits (average number of repeat visits of each visitor), visit duration (average length of stay for each visit), visitor bookmarking behavior (average number of favorite store and product links of each visitor), and visitor attributes (ratio of regular visitors). We also evaluate the dynamic influence of these variables, compare the importance of different measures to sales performance, and examine the two strongest factors in further detail.

Table 1. Existing Literature on Visit Behavior

	Visit behavior					Methods				Data	
	VN	**RV**	**VDU**	**VBB**	**VA**	**Model**	**RE**	**SEM**	**Other**	**Survey**	**SD**
Bhatnagar et al., 2016		✓	✓			✓					✓
Johnson et al., 2004			✓			✓					✓
Moe & Fader, 2004a	✓	✓				✓					✓
Moe & Fader, 2004b		✓				✓					✓
Montgomery et al., 2004			✓			✓					✓
Danaher et al., 2006			✓		✓	✓					✓
Bucklin & Sismeiro, 2003		✓	✓			✓					✓
Panagiotelis et al., 2014			✓			✓					✓
Polites et al., 2012			✓					✓		✓	
Roy et al., 2014			✓					✓		✓	
Wu et al., 2010		✓						✓		✓	
Lin, 2007			✓					✓		✓	
Lin et al., 2010			✓				✓				✓
Rishika et al., 2013	✓	✓			✓		✓				✓
Mallapragada et al., 2016			✓		✓		✓				✓
De Valck et al., 2007		✓					✓			✓	
Dhar & Chang, 2009				✓			✓				✓
Lin, 2014				✓			✓				✓
Sharma & Gupta, 2012	✓								EX		✓
Our study	✓	✓	✓	✓	✓				VARX		✓

Note: VN denotes visitor numbers; RV denotes repeat visits; VDU denotes visit duration; VBB denotes visitor bookmarking behavior; VA denotes visitor attributes; RE denotes regression; SEM denotes structural equation model; SD denotes secondary data; EX denotes experiment; and VARX denotes vector autoregression with exogenous variables.

3 Research Framework

3.1 Data and Measures

We derived our study data from the online retail website Tmall, which is owned by Alibaba and is one of the most important e-commerce websites in China. Tmall, formerly Taobao Mall, was launched in April 2008. As one of the largest business-to-consumer (B2C) platforms, it is used by a large number of Chinese and international retailers to establish storefronts and sell various brand goods. The platform is dedicated to providing products to consumers seeking top-quality brand products. According to Alexa statistics (https://www.alexa.com/topsites), in April 2019, Tmall ranked as the eighth most-visited website in the world. We present the homepage of Tmall in Figure 1. The platform records information on visitors to its online stores, and we collected data from one online store that primarily focuses on the retail sales of pharmaceutical and medical equipment products. The owner of the online store is mainly engaged in drug production, research, development, and related health services and operates one of the largest pharmaceutical e-commerce enterprises in China. We obtained data from December 22, 2014 to June 28, 2015 for a total of 189 days, and the data include information related to customer online behavior, such as bookmarking, visiting, and ratings. In terms of visit behavior, we examined the number of visitors, repeat visits (average number of visits for each visitor), visit duration (average length of stay for each visit), visitor bookmarking behavior (average number of favorite store and product links of each visitor), and visitor attributes (ratio of regular visitors). We also obtained data on sales performance, such as number of paid orders and the amount of paid orders. We divided all variables into three parts: the dependent variables of sales performance, the measures for the independent variable, and the measures for control variables. Table 2 provides a summary of all variables.

Unlike most existing studies that adopt sales as the only dependent variable, in our study, which focuses on various aspects of sales, we identified 10 measures of sales: number (ratio) of paid orders, number (ratio) of suborders, total monetary amount of the paid orders, ratio of the amount of paid orders, number (ratio) of the customers' paid orders, and number (ratio) of products with paid orders. To illustrate these dependent variables, we offer a simple example of the shopping experience of Customer A in an online store: Assume that Customer A selects Products B, C, and D and pays 100 yuan for the three products in one order, which is defined in our dependent variables as a paid order. This paid order includes three products and each product has suborders. Thus, this paid order includes three suborders. In this example, 100 is the amount of the paid order, 1 is the number of the customer's paid order, and 3 is the number of products in the paid order. In contrast to examining the impacts of one product on sales performance, we focus on the sales performance of an entire store and examine its influence on orders, suborders, customers, products, and total payment amounts, which are important indexes of sales performance for online stores (Bezawada & Pauwels, 2013; Cravens & Woodruff, 1973; Wan et al., 2012). Furthermore, we evaluate the ratio of the number of paid orders to total orders (i.e., orders that are made but not paid for), which can reflect the influence of the independent variables on the payment probability related to the customers' purchasing behavior.

Figure 1. Homepage of Tmall in April 2019

Table 2. Summary of Variables

Measures	Variables	Description
Sales performance		
Paid orders	PO_t	The number of paid orders in the online store on day t.
Paid suborders	PSO_t	The number of paid suborders in the online store on day t.
Monetary amount of paid orders	MPO_t	The total monetary amount of paid orders in the online store on day t.
Customers with paid orders	CPO_t	The number of customers with paid orders in the online store on day t.
Products in paid orders	PPO_t	The number of products in paid orders in the online store on day t.
Ratio of paid orders	RPO_t	The ratio of the number of paid orders to the total number of orders in the online store on day t.
Ratio of paid suborders	$RPSO_t$	The ratio of the number of paid suborders to the total number of suborders in the online store on day t.
Ratio of monetary amount of paid orders	$RMPO_t$	The ratio of the monetary amount of paid orders to the monetary amount of total orders in the online store on day t.
Ratio of customers with paid orders	$RCPO_t$	The ratio of customers with paid orders to total customers placing orders in the online store on day t.
Ratio of products in paid orders	$RPPO_t$	The ratio of the number of products in paid orders to the total number of products ordered in the online store on day t.
Independent variables		
Visitors number of online stores	SVO_t	The number of visitors to the online store on day t.
Average visit number of each visitor	AVN_t	The average number of visits of each visitor to the online store on day t.
Average time length of each visit	AST_t	The average length of each visit to the online store on day t.
Average number of favorite store links for each visitor	AFS_t	The average number of store links bookmarked as a favorite by each visitor in the online store on day t.
Average number of favorite product links for each visitor	AFP_t	The average number of product links bookmarked as a favorite by each visitor in the online store on day t.
Ratio of regular visitors	RRV_t	The ratio of regular visitors to total visitors to the online store on day t.
Control variables		
Service rating	SR_t	The average value of the service rating of the online store on day t.
Logistics rating	LR_t	The average value of the logistics rating of the online store on day t.
Product description rating	DR_t	The average value of product description rating of online store on day t.
Google news search	GN_t	The number of Google news searches on day t for the company owning the online store.
Baidu news search	BN_t	The number of Baidu news searches on day t for the company owning the online store.
Month	Mon_t	Months (i.e., January, February, etc.).
Time trend	$Time_t$	An increasing indicator variable denoting the days (1,2,…, 189).

In terms of independent variables, we mainly focused on online consumer behavior. In terms of various online behaviors and our independent variables, we define Online User A as visiting Online Store B on one day. The variable SVO measures the number of users who visit the online store at least once a day. The number of visitors reflects the popularity of the online store, which is cited by existing literature as significantly affecting sales performance (Rishika et al., 2013; Zufryden, 2000). Additionally, if User A repeatedly visits Store B in one day, this frequency suggests User A's strong interest in product(s) in this online store. Thus, we introduce the variable AVN to represent the average number of visits for each visitor in one day. Anderson and Srinivasan (2003) argue that if consumers are unsatisfied with a website, they are less likely to revisit the website and more likely to search for alternative ones. Moe and Fader (2004a) adopt the number of "visits per visitor" to measure the website's ability to attract and retain customers. We also note the length of stay for each visit of User A in Store B, as the duration of each visit may influence the consumer's decision. We use the variable AST to denote the average length of time of each visit, which is an important index that is similar to visit duration in the existing literature and that affects sales performance (Mallapragada et al., 2016; Plaza, 2011). If User A is interested in an online store or the store's product, then he or she might bookmark the store or product as a favorite on his or her personal user page to more easily access the store/product. We use the variables AFS and AFP to measure the average number of store and product links bookmarked as a favorite by visitors on a given day. The visitors' characteristics also represent an important factor, especially the visitor's status as a regular or new customer, which has been proven to significantly affect sales performance in online stores (Berne et al., 2005; Zhang et al., 2018). Thus, we also include the ratio of regular visitors to total visitors (RRV) as another independent variable potentially influencing the sales performance of online stores. After users shop, they may rate the service, product description, or logistics. We thus also control three variables, namely SR, DR and LR, to represent the average rating values for service, product description, and logistics, respectively. Rating is a direct reflection of the customers' experience and has been demonstrated to significantly affect the buying decision of potential customers (Luo et al., 2018). In existing studies, scholars have adopted online ratings to predict product sales performance (Lee et al., 2015).

Figure 2 presents an example of the online store's homepage on Tmall and shows some variables. The three rating variables—SR, DR, and LR—are visible on the homepage, as is the store's bookmarking function that allows users to save the store link as a favorite; AFS denotes the average number of favorite store links for each visitor. The other key variables are not explicitly visible in the figure.

Figure 2. Example of Online Store's Homepage on Tmall

We further illustrate visit behavior variables through the following example. On January 4, 2015, a total of 89,062 visitors visited the online store. The store had a total of 384,024 visits, and the average visit number of each visitor (AVN) was nearly 4.311. The average length of time of each visit (AST) was approximately 40 seconds. The online store and product pages had been set as favorites a total of 353 and 3473 times, respectively, and the average number of favorite store and product links of each visitor (AFS, AFP) were 0.003 and 0.038, respectively. Among the 89,062 visitors, a total of 13,506 had visited the online store before and the ratio of regular visitors was 0.151.

We also controlled some other variables in our study. First, we identified the number of news reports generated by Google and Baidu searches between December 22, 1914 and June 28, 2015, because news reports have been widely adopted in predicting the performance of stocks and product sales (Babić Rosario et al., 2016; Luo et al., 2015; Tang et al., 2014). The news report number denotes news attention in social media, and we believe that this number can significantly affect sales performance and therefore used it as a control variable. We used the name of the company that owns the online stores to search for news reports in Baidu and Google. We counted the number of news reports related to the company on each day. It has been widely reported that there is a significant difference in buying behavior in different months (Du & Hu, 2015; Luo et al., 2016). Thus, we also include the month dummy variable as a control variable. Moreover, we also added time trend, measuring the study period day, as a control variable in the model (Heerde et al., 2013; McLean & Pontiff, 2016).

3.2 Research models

We adopted the VARX model, a time-series analysis method, to investigate the relationships between visit behavior metrics and sales performance measures. Unlike the vector autoregression (VAR) model, the VARX model controls the impacts of exogenous variables and we included the news number, month, and time trend. Moreover, the VARX model allowed us to analyze more than one evolving variable: each variable is treated symmetrically and has an equation with its own lags and other variables. Thus, based on the generalized impulse response functions (Pesaran & Shin, 1998), the model can analyze the dynamic and cumulative effects of visit behavior metrics on sales performance. Compared with other static models, the VARX model is particularly useful in tracking dynamic relationships. The generalized forecast error variance decomposition (Koop et al., 1996; Pesaran & Shin, 1998) enabled us to examine the relative importance of different variables. Many previous studies have adopted the VARX model to examine the time-series impacts of independent variables (Adomavicius et al., 2012; Luo & Zhang, 2013; Luo et al., 2013; Tirunillai & Tellis, 2012). We follow these studies in using the VARX model in our empirical study. The variables include sales performance, the independent variables (*SVO*, *AVN*, *AST*, *AFS*, *AFP*, *RRV*), and the control metrics (*DR*, *SR*, *LR*, *GN*, *BN*, *Mon*, *Time*). The VARX model is specified below:

$$\begin{bmatrix} DV_t \\ SVO_t \\ AVN_t \\ AST_t \\ AFS_t \\ AFP_t \\ RRV_t \\ DR_t \\ SR_t \\ LR_t \end{bmatrix} = \begin{bmatrix} \alpha_1+\delta_1 t \\ \alpha_2+\delta_2 t \\ \alpha_3+\delta_3 t \\ \alpha_4+\delta_4 t \\ \alpha_5+\delta_5 t \\ \alpha_6+\delta_6 t \\ \alpha_7+\delta_7 t \\ \alpha_8+\delta_8 t \\ \alpha_9+\delta_9 t \\ \alpha_{10}+\delta_{10} t \end{bmatrix} + \sum_{k=1}^{K} \begin{bmatrix} \phi_{1,1}^k \cdots \phi_{1,10}^k \\ \phi_{2,1}^k \cdots \phi_{2,10}^k \\ \phi_{3,1}^k \cdots \phi_{3,10}^k \\ \phi_{4,1}^k \cdots \phi_{4,10}^k \\ \phi_{5,1}^k \cdots \phi_{5,10}^k \\ \phi_{6,1}^k \cdots \phi_{6,10}^k \\ \phi_{7,1}^k \cdots \phi_{7,10}^k \\ \phi_{8,1}^k \cdots \phi_{8,10}^k \\ \phi_{9,1}^k \cdots \phi_{9,10}^k \\ \phi_{10,1}^k \cdots \phi_{10,10}^k \end{bmatrix} \cdot \begin{bmatrix} DV_{t-k} \\ SVO_{t-k} \\ AVN_{t-k} \\ AST_{t-k} \\ AFS_{t-k} \\ AFP_{t-k} \\ RRV_{t-k} \\ DR_{t-k} \\ SR_{t-k} \\ LR_{t-k} \end{bmatrix} + \begin{bmatrix} \tau_{1,1} \cdots \tau_{1,4} \\ \tau_{2,1} \cdots \tau_{2,4} \\ \tau_{3,1} \cdots \tau_{3,4} \\ \tau_{4,1} \cdots \tau_{4,4} \end{bmatrix} \cdot \begin{bmatrix} GN_t \\ BN_t \\ Mon_t \\ Time_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \\ \varepsilon_{8t} \\ \varepsilon_{9t} \\ \varepsilon_{10t} \end{bmatrix} \quad (1)$$

where *DV* represents the store's sales performance, including *PO, MPO, CPO, PPO, RPO, RPSO, RMPO, RCPO, RPPO*; $\alpha_i\left(i=1,2,\cdots,10\right)$ is a constant; $\delta_i, \phi_{i,j}^k\left(i, j=1,2,\cdots,10\right)$ are coefficients; $\tau_{i,j}\left(i, j=1,2,3,4\right)$ is the coefficient of the exogenous variable; *K* is the lag length, and $\varepsilon_i\left(i=1,2,\cdots,10\right)$ represents the white-noise residual.

We use 10 sales performance variables and test the dependent variable in the VARX model one by one. Thus, we estimate 10 VARX models corresponding to 10 sales performance variables. The lag order of the VARX model is always chosen by the value of Schwartz's Bayesian information criterion (SIC) and the final prediction error (FPE) (Luo et al., 2013; Tirunillai & Tellis, 2012). We selected the lag order with the minimized SIC and FPE for our model, and the clear results of lag order selection are provided in Table 20 in the Appendix. We also tested the model's stationarity, and the results are presented in Figure 4 in the Appendix. We then ran the cointegration test, the details of which are presented in Table 21 in the Appendix.

4 Empirical Results

We first present the statistics of the key variables in Table 3 and conduct the augmented Dickey-Fuller (ADF) test to check whether the variables are evolving or stationary. The results of the ADF test are provided in Table 4, and most variables are less than the critical value of -2.876, ranging from -6.976 to -2.918. This finding indicates that the null hypothesis (the variable has a unit root and is not stable) is rejected at the 95% confidence level and that the variables are stable. We adopt the first difference for RPO, and the ADF test result of the first difference data is -19.655, suggesting that RPO does not cointegrate in equilibrium. Before addressing the main empirical analysis, we first explain the potential correlation problem of the key variables. We know that the key variables measure the differences or similarities in aspects of visit behavior. SVO is the number of visitors, AVN is the average number of visits for each visitor, AST is the average length of stay of each visit, and AFS and AFP are the average number of favorite store and product links of each visitor, respectively. These variables thus measure the popularity of the online store or products to some extent. Specifically, AFS and AFP, which are very similar concepts, indicate the store's popularity with visitors and represent the degree of potential purchase intention. The correlation of AFS and AFP in our study is nearly 0.6, which is consistent with the above discussion. RRV is the ratio of regular visitors to total visitors and, if the regular customers stay longer or visit more times, this may lead to a high correlation between RRV and AST or AVN. The actual correlation of RRV and AVN in our study is approximately 0.6, while the correlation value of RRV and AST is just -0.3. These results indicate that regular customers have higher numbers of repeat visits and shorter visit duration times. Since some high correlations exist among the key variables, we performed the multicollinearity test in the regression with the key variables; the VIF values are mostly below 4. Moreover, the VARX model can handle high correlations among key variables. For example, Luo et al. (2013) adopted the VARX model to test the impacts of social media metrics on the firms' equity value. The key measurements included product rating volume, blog posts volume, Google search volume, and firm website view volume. These key variables all demonstrate the popularity of the firm and have high correlations, which can be solved by the VARX model. A similar situation can be seen in the study by Tirunillai and Tellis (2012).

Table 3. Statistics of Key Variables

DV	Mean	Max	Min	Std	IV	Mean	Max	Min	Std
PO	6151.7	10927	521	1653.73	SVO	111594.6	345723	30145	37885.5
PSO	8372.6	15864	727	2220.60	AVN	3.6	4.8	2.3	0.504
MPO	432451.9	1036654	41109.1	128509	AST	55.0	118.8	36	13.4
CPO	5738.1	10475	484	1548.43	AFS	0.003	0.011	0.000	0.0.001
PPO	13243.2	24493	1179	3518.48	AFP	0.032	0.049	0.005	0.007
RPO	0.850	0.903	0.727	0.024	RRV	0.140	0.176	0.056	0.022
RPSO	0.872	0.907	0.748	0.023					
RMPO	0.754	0.878	0.506	0.054					
RCPO	0.905	0.945	0.775	0.025					
RPPO	0.848	0.887	0.630	0.027					

Table 4. Dickey-Fuller Test for Unit Root

DV	Original	First difference	IV	Original
PO	-3.252		SVO	-6.447
PSO	-3.249		AVN	-3.732
MPO	-4.928		AST	-3.304
CPO	-3.301		AFS	-6.244
PPO	-3.232		AFP	-6.474
RPO	-2.703	-19.655	RRV	-6.976
RPSO	-2.918			
RMPO	-6.754			
RCPO	-3.868			
RPPO	-3.666			

Note: Augmented Dickey-Fuller (ADF) test statistic critical value: -2.876 (5% level of significance).

Table 5. Granger Tests and Model Index

	SVO	AVN	AST	AFS	AFP	RRV	ALL	R^2	Adj-R^2	*F*
PO	0.992	0.068*	0.417	0.785	0.702	0.897	0.000***	0.718	0.695	31.260
PSO	0.549	0.032**	0.457	0.730	0.807	0.861	0.000***	0.722	0.700	31.930
MPO	0.569	0.006***	0.252	0.945	0.690	0.679	0.000***	0.509	0.469	12.713
CPO	0.997	0.058*	0.349	0.794	0.728	0.917	0.000***	0.706	0.682	29.543
PPO	0.098*	0.010***	0.377	0.382	0.950	0.943	0.002***	0.723	0.700	32.063
RPO	0.954	0.006***	0.887	0.100*	0.687	0.909	0.000***	0.772	0.754	41.636
RPSO	0.212	0.000***	0.575	0.346	0.100*	0.682	0.001***	0.649	0.620	22.676
RMPO	0.229	0.205	0.100*	0.246	0.548	0.051*	0.017**	0.208	0.143	3.217
RCPO	0.327	0.001***	0.792	0.099*	0.787	0.085*	0.000***	0.869	0.858	81.525
RPPO	0.007***	0.086*	0.832	0.228	0.309	0.003***	0.000***	0.403	0.354	8.285

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.1 Granger Test

Following Tirunillai and Tellis (2012), we conducted a Granger test and the results are reported in Table 5. The results show that many variables have significant relationships with the sales performance of online stores. Among the different metrics, the average visit number (AVN) most significantly affects sales performance and can strongly influence PO, PSO, MPO, CPO, PPO, RPO, RPSO, RCPO, and RPPO (p = 0.068, 0.032, 0.006, 0.058, 0.010, 0.006, 0.000, 0.001 and 0.086, respectively). RRV is also sufficiently significant to affect RMPO, RCPO, and RPPO (p = 0.051, 0.085 and 0.003). SVO and AFS are significantly related to two of the dependent variables: SVO strongly affects PPO (0.0098) and RPPO (0.007), while AFS strongly influences RPO (0.100) and RCPO (0.099). AST only has a strong relationship with RMPO (0.100), and AFP only has a strong relationship with RPSO (0.100). Moreover, we also provide the part regression index (R^2, Adj-R^2, and F value) of VARX in Table 5.

4.2 Generalized Impulse Response Functions

With the generalized impulse response functions (GIRFs), we investigated the dynamics of independent variables. In this process, the GIRFs adopted the VARX estimates to trace the impact of a unit shock of an independent variable (visit behavior metric) on the sales performance over subsequent periods. We determined the standard errors by simulating the fitted VARX model by using the Monte Carlo method with 1000 runs and were able to obtain the statistical significance of the parameters. We defined the immediate impact as the average time taken to reach the peak point in the third time period, as shown in Figure 3, and thus chose the third time period as the immediate impact period. To capture the total effect of visit behavior metrics on sales performance, we followed Luo et al. (2013) and defined the accumulated duration as a period of 20 days. Figure 3 shows the immediate response of RPO to six main independent variables. In terms of AVN, AFS, AFP, and RRV, RPO first increases and peaks in the initial periods and then gradually decreases. For the other variables (SVO and AST), RPO first decreased below 0 in the initial periods and then gradually increased.

Table 6 reports the results of the immediate impact of various independent variables on 10 dependent variables of sales performance. First, we found that AVN has a strong and positive effect on all dependent variables, including PO (130.853, $p < 0.1$), PSO (212.973, $p < 0.1$), MPO (15572.400, $p < 0.01$), CPO (118.461, $p < 0.1$), PPO (379.946, $p < 0.01$), RPO (0.004, $p < 0.01$), RPSO (0.002, $p < 0.01$), RMPO (0.005, $p < 0.1$), RCPO (0.003, $p < 0.01$) and RPPO (0.004, $p < 0.01$). In the short term, an unexpected increase in AVN predicts a surge in RPO by 0.004 and RPSO by 0.002. Moreover, SVO, AST, and RRV exert a significantly positive influence on some dependent variables. In the short term, SVO and AST mainly have a positive predictive value on PO, PSO, MPO, CPO, and PPO, while RRV is positively related immediately with RPO, RMPO, RCPO, and RPPO. However, AFS and AFP have an insignificant influence on most dependent variables: AFS only significantly influences RPSO, and AFP only significantly influences RPO and RCPO. Table 7 presents the accumulated impact of the independent variables on sales performance metrics. In the long term, only AVN has a significantly positive relationship with most of the dependent variables, including PO (2650.553, $p < 0.1$), PSO (3651.472, $p < 0.1$), MPO (116062.500, $p < 0.1$), CPO (2416.506, $p < 0.05$), PPO (6033.721, $p < 0.05$), RPO (0.045, $p < 0.01$), RPSO (0.037, $p < 0.01$), RCPO (0.058, $p < 0.05$), and RPPO (0.026, $p < 0.05$). SVO strongly affects only RMPO (0.021, $p < 0.1$), AFP strongly affects only RPO (0.025, $p < 0.1$), and RCPO (0.036, $p < 0.1$) and RRV strongly affect only RPO (0.023, $p < 0.1$). All the other relationships are not significant.

To further clarify our results, we found that AVN has a great impact on the sales performance variables and found that the impact is significant in two tests. Specifically, in the Ganger test, AVN is significantly and positively related to all dependent variables except RMPO. Similarly, AVN shows a significant positive predictive relationship with all dependent variables in the short term and with all dependent variables except RMPO in the long term. The consistent results of AVN in the Granger test and the impulse response function indicate that the average visit number of each visitor can strongly increase the sales performance of online stores. For example, an unexpected increase in AVN predicts a rise in RPPO by 0.004 ($p < 0.01$) in the short term and by 0.026 ($p < 0.05$) in the long term. The Granger test also shows that RRV can significantly affect RMPO, RCPO, and RPPO. Similarly, in the immediate impulse response function, RRV has strong and positive relationships to RMPO, RCPO and RPPO. However, RRV does not significantly influence these three variables in the long term. Based on these results, we conclude that the ratio of regular visitors to total visitors can also increase the sales performance of online stores, especially in terms of the ratio of the monetary amount of paid orders, the ratio of customers of paid orders, and the ratio of products of paid orders.

Table 6. Immediate Impulse Response of Sales Performance to Independent Variables

	SVO	**AVN**	**AST**	**AFS**	**AFP**	**RRV**
PO	163.575*	130.853*	245.043***	35.691	72.509	-42.489
PSO	206.560*	212.973*	274.718***	64.414	113.840	-36.246
MPO	16136.010**	15572.400***	14122.900**	-1346.929	-2796.950	-3968.511
CPO	157.495*	118.461*	236.411***	29.290	63.813	-42.121
PPO	275.802*	379.946***	380.409***	153.070	211.143	-5.230
RPO	-0.001	0.004***	-0.001	0.001	0.002*	0.003**
RPSO	0.000	0.002***	0.000	0.002*	0.002	0.001
RMPO	0.018***	0.005*	0.011***	-0.001	0.002	0.006*
RCPO	0.000	0.003***	-0.001	0.001	0.002*	0.002*
RPPO	0.003	0.004***	-0.001	0.000	0.001	0.004***
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$						

Table 7. Accumulated Impulse Response of Sales Performance to Independent Variables

	SVO	**AVN**	**AST**	**AFS**	**AFP**	**RRV**
PO	304.520	2650.553*	-344.692	1017.945	1867.220	784.317
PSO	518.399	3651.472*	-499.053	1446.353	2523.900	1011.322
MPO	66268.420	116062.500*	14125.390	36219.250	58373.470	19241.310
CPO	316.877	2416.506**	-278.708	908.460	1693.682	703.507
PPO	758.135	6033.721**	-849.341	2737.314	4195.674	1738.695
RPO	-0.010	0.045***	-0.018	0.014	0.025*	0.023*
RPSO	-0.005	0.037***	-0.014	0.012	0.020	0.017
RMPO	0.021*	0.012	0.012	-0.008	0.003	-0.001
RCPO	-0.021	0.058**	-0.027	0.017	0.036*	0.031
RPPO	0.004	0.026**	-0.006	0.007	0.012	0.011
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$						

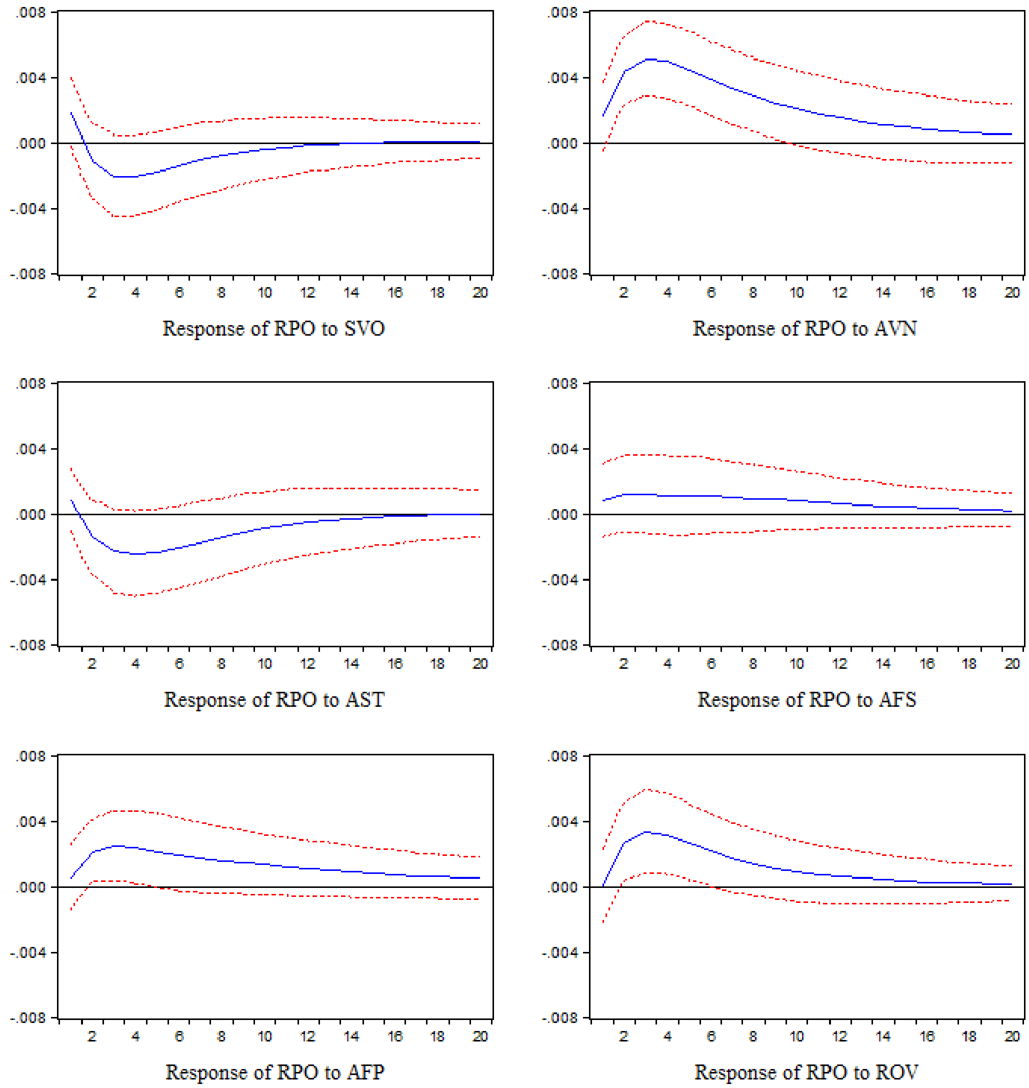

Figure 3. Immediate Response of RPO to Independent Variables

Regarding SVO and AST, the results are somewhat inconsistent. In terms of the Granger test, SVO significantly affects only PPO and RPPO, and AST significantly affects only RMPO. For the impulse response functions, in the short term, both SVO and AST have a strong and positive relationship with most sales performance metrics, including PO, PSO, MPO, CPO, PPO, RMPO; however, most of these relationships are not significant in the long term. As regards the inconsistent results in both the Granger test and the impulse response function, these two tests have different assumptions, mechanisms, and functions that may lead to different results. The Granger test mainly focuses on the existence of the relationship between independent variables and sales performance variables, while the impulse response function mainly focuses on the estimation of the net effects of a change in an independent variable on sales performance metrics. Furthermore, for the immediate impulse response function, we chose the third period as the short-term or immediate effect for all independent variables because the effects generally reached their peak near the third period. However, the impulse response functions are different across different dependent variables and independent variables, which may also lead to different results. Finally, in both the Granger test and the impulse response functions, AFS and AFP did not significantly affect most sales performance metrics.

4.3 Relative Importance of Sector Interactive Metrics

Based on the generalized forecast error variance decomposition (GFEVD), we assessed the relative importance of dependent variables on the impacts on store sales performance and obtained the GFEVD estimates from the following algorithm:

$$\theta_{i,j}(t) = \frac{\sum_{k=0}^{t}\left(\psi_{i,j}(k)\right)^2}{\sum_{k=0}^{t}\sum_{j=0}^{m}\left(\psi_{i,j}(t)\right)^2},\ i, j = 1,\cdots,m.$$

The GFEVD provides the relative importance values of the independent variables that were established in twenty days. This value should reduce the short-term functions, as suggested by previous research (Hong & Stein, 1999; Tirunillai & Tellis, 2012).

The relative importance of variables in determining the dependent variables is shown in Table 8. The results show that AVN is the most important metric that affects sales performance variables, followed by SVO and then AFS and RRV; AFP and AST are the least important variables. The results show, on average, the order of importance as AVN (16.599%), SVO (5.507%), AFS (0.842%), RRV (0.645%), AFP (0.605%) and AST (0.354%). We compared the value of different metrics in relation to their influence on the sales performance variables and present the comparison results in Table 9.

Table 8. Generalized Forecast Error Variance Decomposition (GFEVD) of Sales Performance

	SVO	**AVN**	**AST**	**AFS**	**AFP**	**RRV**
PO	10.546	13.795	0.143	0.079	0.617	0.067
PSO	6.421	16.088	0.092	0.127	0.641	0.074
MPO	4.078	22.266	0.411	0.043	0.372	0.307
CPO	10.482	14.038	0.225	0.068	0.589	0.067
PPO	3.688	22.020	0.195	0.706	0.634	0.077
RPO	6.840	19.524	0.363	1.837	0.496	0.129
RPSO	1.213	21.399	0.161	1.389	1.346	0.143
RMPO	0.424	4.372	1.308	0.971	0.319	0.953
RCPO	10.430	16.227	0.351	1.949	0.296	2.149
RPPO	0.947	16.265	0.287	1.251	0.742	2.487
Average	5.507	16.599	0.354	0.842	0.605	0.645

Table 9. Comparison Test

	SVO	AVN	AST	AFS	AFP	RRV
SVO		-5.227***	3.872***	3.471***	3.727***	3.570***
AVN	5.227***		9.167***	9.319***	9.653***	8.947***
AST	-3.872***	-9.167***		-2.009*	-1.419	-1.013
AFS	-3.471***	-9.319***	2.009*		0.950	0.754
AFP	-3.727***	-9.653***	1.419	-0.950		-0.122
RRV	-3.570***	-8.947***	1.013	-0.754	0.122	
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$						

AVN accounts for the largest proportion of variance of sales performance, and its variance is significantly larger than that of SVO (5.227, $p < 0.01$), AST (9.167, $p < 0.01$), AFS (9.319, $p < 0.01$), AFP (9.653, $p < 0.01$), and RRV (8.947, $p < 0.01$). SVO's variance represents the second largest proportion and is also significantly larger than that of AST (3.872, $p < 0.01$), AFS (3.471, $p < 0.01$), AFP (3.727, $p < 0.01$), and RRV (3.570, $p<0.01$). Among the other variables, AFS outperforms only AST (2.009, $p < 0.1$) in explaining sales performance and is not significantly different from the other three variables. Compared with the other three variables without significant differences, AFS, AFP and RRV are less important for predicting the variance of sales performance.

Based on the results of the Granger test, generalized impulse response functions, and relative importance analysis, we discuss the underlying mechanism of relationships between visit behavior metrics and sales performance. First, the impacts of some visit behavior metrics, such as AVN and SVO, are very strong and positively related to the store's sales performance. AVN is the average visit number of each visitor to the online store and is the most important metric for explaining sales performance variance. We assume that if users visit one online store many times, it suggests that the online store or its products are very attractive to these users, which may be one of the most critical factors influencing their purchase decision. In contrast, if consumers do not revisit an online store, it might be because they do not like the store or are not considering buying anything from this store. Thus, the more frequently a user visits an online store (representing a high AVN value and high attractiveness of the online store), the more likely the user is to make a purchase from the online store. SVO, which represents the number of store visitors, also has a strong impact on sales performance and accounts for the second largest impact on sales performance variance. Comparing Online Store A and Online Store B, if there are more visitors to Store A than to Store B, with the other factors constant, we can assume that Store A is more popular and better known among consumers than Store B. The popularity of an online store is another important factor affecting sales performance. Moreover, if there are more visitors to Store A and the purchasing probability is the same among visitors, there will be more sales at Store A than at Store B. Thus, it is reasonable to assume that our results indicate significant correlations between visit behavior metrics and online store sales performance.

Second, some other visit behavior variables do not have strong impacts on sales performance. For example, our results show that AFS and AFP only slightly affect some sales performance variables, do not exert a strong effect on most dependent variables, and explain less than one percent of sales performance variance. Since we examine different visit behavior metrics in a single model, influence on sales performance may be dominated by other real factors. For example, if we were to test the relationship between AFS and sales performance only, we may observe strong effects. However, by examining a variety of visit behavior metrics in a single model, we can determine which factors (AVN, SVO) are most important and dominate the influence on sales performance as compared to other factors. Thus, our comprehensive model using different visit behavior metrics is capable of identifying the most important factors affecting the sales performance.

4.4 Additional Test

SVO and AVN are the most important factors in explaining sales performance. In Model (2) below, we further use visitor numbers and the average number of visits of each visitor to the store's homepage (HPVO, AVNHP) and product page (PVO, AVNP), respectively, as alternative measures to not only test the robustness of our empirical results but also to compare the different performance of homepage visitors and product page visitors. We define $HPVO_t$ as the number of visitors to the homepage of the online store on day *t*, $AVNHP_t$ as the average number of visits of each visitor to the homepage of the online store on day *t*, PVO_t as the number of visitors to the product page of the online store on day *t*, and $AVNP_t$ as the average number of visits of each visitor to the product page of the online store on day t. We retain the other independent variables and control variables.

We first tested the stationarity of four new variables (HPVO, AVNHP, PVO, and AVNP), using the original form of HPVO (-4.837), PVO (-6.477), and the first difference of AVNHP (-12.804), AVNP (-11.926). The lag order was also selected by the value of FPE and SIC, suggesting a lag order of 1. We then processed the model stationarity test and cointegration test before conducting the following analysis. Concerning the results of the Granger test, Table 10 shows the strong influence of independent variables on sales performance, especially the influence of HPVO, which is significantly related to all dependent variables except RPPO and RMPO. PVO significantly influences PO (0.094), MPO (0.054), CPO (0.092), RPO (0.004), RPSO (0.005), RCPO (0.017); Furthermore, AVNP is strongly related to PSO (0.086), MPO (0.017), PPO (0.044), RPO (0.016), RPSO (0.000), and RCPO (0.001). However, AVNHP strongly affects only RPO (0.100) and RPSO (0.057). We then applied the immediate and accumulative impulse response of the independent variables to the sales performance variables. We also defined the time period as the immediate impact period when the effects of most independent variables reach their peak and determined 20 days to be the accumulative impact time period.

$$\begin{bmatrix} DV_t \\ HPVO_t \\ AVNHP_t \\ PVO_t \\ AVNP_t \\ AST_t \\ AFS_t \\ AFP_t \\ RRV_t \\ DR_t \\ SR_t \\ LR_t \end{bmatrix} = \begin{bmatrix} \alpha_1 + \delta_1 t \\ \alpha_2 + \delta_2 t \\ \alpha_3 + \delta_3 t \\ \alpha_4 + \delta_4 t \\ \alpha_5 + \delta_5 t \\ \alpha_6 + \delta_6 t \\ \alpha_7 + \delta_7 t \\ \alpha_8 + \delta_8 t \\ \alpha_9 + \delta_9 t \\ \alpha_{10} + \delta_{10} t \\ \alpha_{11} + \delta_{11} t \\ \alpha_{12} + \delta_{12} t \end{bmatrix} + \sum_{k=1}^{K} \begin{bmatrix} \phi_{1,1}^k \cdots \phi_{1,12}^k \\ \phi_{2,1}^k \cdots \phi_{2,12}^k \\ \phi_{3,1}^k \cdots \phi_{3,12}^k \\ \phi_{4,1}^k \cdots \phi_{4,12}^k \\ \phi_{5,1}^k \cdots \phi_{5,12}^k \\ \phi_{6,1}^k \cdots \phi_{6,12}^k \\ \phi_{7,1}^k \cdots \phi_{7,12}^k \\ \phi_{8,1}^k \cdots \phi_{8,12}^k \\ \phi_{9,1}^k \cdots \phi_{9,12}^k \\ \phi_{10,1}^k \cdots \phi_{10,12}^k \\ \phi_{11,1}^k \cdots \phi_{11,12}^k \\ \phi_{12,1}^k \cdots \phi_{12,12}^k \end{bmatrix} \cdot \begin{bmatrix} DV_{t-k} \\ HPVO_{t-k} \\ AVNHP_{t-k} \\ PVO_{t-k} \\ AVNP_{t-k} \\ AST_{t-k} \\ AFS_{t-k} \\ AFP_{t-k} \\ RRV_{t-k} \\ DR_{t-k} \\ SR_{t-k} \\ LR_{t-k} \end{bmatrix} + \begin{bmatrix} \tau_{1,1} \cdots \tau_{1,4} \\ \tau_{2,1} \cdots \tau_{2,4} \\ \tau_{3,1} \cdots \tau_{3,4} \\ \tau_{4,1} \cdots \tau_{4,4} \end{bmatrix} \cdot \begin{bmatrix} GN_t \\ BN_t \\ Mon_t \\ Time_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \\ \varepsilon_{8t} \\ \varepsilon_{9t} \\ \varepsilon_{10t} \\ \varepsilon_{11t} \\ \varepsilon_{12t} \end{bmatrix} \quad (2)$$

Table 10. Granger Tests and Model Index

	HPVO	**AVNHP**	**PVO**	**AVNP**	**AST**	**AFS**	**AFP**	**RRV**	**ALL**	**R2**	**Adj-R2**	**F**
PO	0.027**	0.877	0.094*	0.156	0.205	0.893	0.606	0.746	0.000***	0.725	0.699	27.987
PSO	0.020**	0.803	0.158	0.086*	0.220	0.915	0.684	0.747	0.002***	0.730	0.704	28.700
MPO	0.002***	0.300	0.054*	0.017**	0.037**	0.934	0.663	0.804	0.000***	0.535	0.492	12.245
CPO	0.024**	0.914	0.092*	0.134	0.160	0.898	0.625	0.734	0.000***	0.714	0.687	26.488
PPO	0.025**	0.651	0.409	0.044**	0.204	0.696	0.820	0.993	0.001***	0.730	0.704	28.673
RPO	0.048**	0.100*	0.004***	0.016**	0.865	0.194	0.156	0.001***	0.000***	0.369	0.309	6.207
RPSO	0.000***	0.057*	0.005***	0.000***	0.039**	0.421	0.100*	0.504	0.000***	0.691	0.662	23.791
RMPO	0.111	0.539	0.432	0.284	0.056*	0.267	0.575	0.182	0.016**	0.222	0.148	3.027
RCPO	0.010***	0.310	0.017**	0.001***	0.175	0.187	0.776	0.029**	0.000***	0.875	0.864	74.647
RPPO	0.593	0.837	0.456	0.100*	0.693	0.251	0.346	0.006***	0.000***	0.406	0.350	7.257

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Tables 11 and 12 present the immediate and accumulative impulse response results, respectively, and we found that the independent variables exert significant impacts on sales performance. For example, HPVO has a significant positive predictive relation with the following variables: with PO by 354.414 ($p < 0.01$) in the short term, and by 2222.124 ($p < 0.1$) in the long term; with MPO by 27324.670 ($p < 0.01$) in the short term, and by 185661.400 ($p < 0.01$) in the long term; with CPO by 333.557 ($p < 0.01$) in the short term, and by 2079.158 ($p < 0.1$) in the long term; with PPO by 713.887 ($p < 0.01$) in the short term, and by 4834.585 ($p < 0.1$) in the long term; and with RMPO by 0.019 ($p < 0.01$) in the short term, and by 0.040 ($p < 0.1$) in long term. Finally, we evaluated GFEVD and report the results in Table 13. We also compared the different variables in illustrating sales performance and present the results in Table 14. Outperforming most other variables, PVO, AVNP, and AVNHP account for the most important factors explaining sales performance. These results are similar to the above analysis in Sections 4.1- 4.3 and support the robustness of our results.

Table 11. Immediate Impulse Response of Sales Performance to Independent Variables

	HPVO	AVNHP	PVO	AVNP	AST	AFS	AFP	RRV
PO	354.414***	94.503*	154.360**	128.281*	63.141	16.160	55.471	-56.747
PSO	484.954***	149.152*	192.721*	207.056**	66.436	37.701	90.350	-55.605
MPO	27324.670***	-1067.468	13564.410*	5621.967	11330.990*	-303.514	-2378.850	-4658.424
CPO	333.557***	86.453*	148.541**	117.049*	64.452	12.055	48.632	-55.903
PPO	713.887***	286.785**	256.618	366.019*	99.889	111.849	172.930	-35.378
RPO	0.004***	0.000	0.002***	0.000	0.001	0.001	0.000	0.001*
RPSO	0.002**	0.002**	0.001	0.002**	0.000	0.001	0.001	0.001
RMPO	0.019***	-0.001	0.018***	0.006*	0.001	0.000	0.002	0.006*
RCPO	0.003***	0.001	0.002**	0.001	0.001	0.000	0.000	0.000
RPPO	0.003	0.001	0.003*	0.004***	0.002	0.000	0.000	-0.001
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$								

Table 12. Accumulated Impulse Response of Sales Performance to Independent Variables

	HPVO	AVNHP	PVO	AVNP	AST	AFS	AFP	RRV
PO	2222.124*	2452.331*	605.189	2075.189*	45.498	667.580	1640.460	250.794
PSO	3088.242	3534.866*	881.829	2859.464*	31.561	982.682	2242.174	321.562
MPO	185661.400***	104323.300	85637.240*	89459.520	30584.740	7452.047	37494.980	-23565.010
CPO	2079.158*	2244.765*	596.046	1891.405*	79.246	582.122	1482.714	204.085
PPO	4834.585*	6198.947**	1440.446	4565.217*	140.290	1799.042	3639.715	549.681
RPO	-0.004	-0.001	0.005***	0.006***	-0.006	0.003	0.005**	0.005***
RPSO	0.016	0.021	-0.004	0.036***	-0.014	0.010	0.018	0.013
RMPO	0.040*	0.015	0.023*	0.011	0.013	-0.013	-0.001	-0.008
RCPO	0.007	0.023	-0.020	0.058***	-0.028	0.017	0.036**	0.029**
RPPO	0.016	0.022	0.004	0.024*	-0.005	0.004	0.011	0.007
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$								

Table 13. Generalized Forecast Error Variance Decomposition (GFEVD) of Sales Performance

	HPVO	AVNHP	PVO	AVNP	AST	AFS	AFP	RRV
PO	1.402	9.582	8.356	3.424	0.369	0.167	1.897	0.043
PSO	0.608	10.372	6.303	4.370	0.334	0.123	2.029	0.056
MPO	2.224	6.053	14.593	5.539	0.934	0.547	0.726	0.045
CPO	1.245	9.446	8.702	3.505	0.471	0.184	1.826	0.040
PPO	0.064	13.268	5.850	6.153	0.547	0.120	2.387	0.033
RPO	2.398	0.312	5.734	0.685	0.700	0.283	0.455	1.437
RPSO	1.889	2.669	14.729	10.399	0.402	1.618	1.085	0.330
RMPO	1.438	0.785	2.379	1.619	1.758	1.091	0.327	0.319
RCPO	2.187	2.243	12.529	11.960	0.117	1.550	0.456	2.054
RPPO	2.603	3.923	3.809	7.226	0.369	1.369	0.866	1.700
Average	1.606	5.865	8.298	5.488	0.600	0.705	1.205	0.606

Table 14. Comparison test

	HPVO	AVNHP	PVO	AVNP	AST	AFS	AFP	RRV
HPVO		-2.586**	-5.016***	-3.465***	3.374***	4.176***	0.843	4.874***
AVNHP	2.586***		-1.199	0.199	3.529***	3.267***	3.853***	3.273***
PVO	5.016***	1.199		2.487**	5.354***	5.675***	5.000***	5.423***
AVNP	3.465***	-0.199	-2.487**		3.979***	4.719***	3.622***	4.550***
AST	3.374***	-3.529***	-5.354***	-3.979***		-0.424	-1.840*	-0.017
AFS	4.176***	-3.267***	-5.675***	-4.719***	0.424		-1.253	0.463
AFP	0.843	-3.853***	-5.000***	-3.622***	1.840*	1.253		1.352
RRV	4.874***	-3.273***	-5.423***	-4.550***	0.017	-0.463	-1.352	
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$								

4.5 Robustness Test

To check the consistency of our empirical results, we first removed some independent variables and used the VARX model to demonstrate the consistency of our main results. To do this, we removed AST and AFP, which had the least influence on the variance of sales performance. AFP has the highest correlation with AFS (nearly 0.6), and AST has the highest correlation with SVO (about 0.6). We also checked the VIF values of the independent variables because, as indicated by the previous literature, the VIF value is also a widely used criterion for selecting variables (Doetterl et al., 2015; Johnson & LeBreton, 2004; Kock & Lynn, 2012). Since SVO and AVN are two of the most important variables affecting sales performance, we retained SVO and AVN in our model, and thus mainly compared the other four independent variables (AST, AFP, AFS and ROV). In the simple regression, the values of AST and AFP were approximately 3, which is larger than that of the other two independent variables (nearly 2). We kept the other four main independent variables (SVO, AVN, AFS, and RRV) and all other control variables in the VARX models. In consistency with our main analysis method, we also performed the Granger test, determined the dynamic influence of the independent variables on sales performance by using the generalized impulse response functions, and performed the relative importance analysis of different visit behavior variables through the use of generalized forecast error variance decomposition (GFEVD). The results are presented in the following Tables 15-19.

Table 15 provides the Granger test results, showing the strong influence of the four variables on the sales performance measurements. AVN strongly affects nearly all dependent variables except RMPO, followed by SVO and RRV. SVO is significantly related to PPO (0.071), RPO (0.000), RPSO (0.053), RMPO (0.013), RPPO (0.000), and RRV is significantly related to RPO (0.002), RMPO (0.011), RCPO (0.093), RPPO (0.002). However, AFS significantly affects only RPSO (0.090) and RPPO (0.070). Next, regarding the impulse response analysis in Tables 16 and 17, AVN significantly affects all sales performance variables in the short term and sales performance variables except RMPO in the long term. SVO and RRV have strong impacts on most dependent variables in the short term but on only some dependent variables in the long term. AFS significantly influences only RPSO in the short term and does not significantly influence sales performance in the long term. Finally, Tables 18 and 19 present the relative importance analysis results. Compared with SVO (3.876, $p < 0.01$), AFS (6.244, $p < 0.01$) and RRV (5.725, $p < 0.01$), AVN explains, on average, nearly 15.279% of the variance of sales performance, which represents the largest proportion. SVO accounts for the second largest sales performance variation (5.007%), which is also significantly larger than AFS (3.509, $p < 0.01$) and RRV (3.173, $p < 0.05$). RRV and AFS explain 0.985% and 0.737% of the variance of sales performance, respectively.

Table 15. Granger Tests and Model Index

	SVO	AVN	AFS	RRV	ALL	R^2	Adj-R^2	F
PO	0.998	0.083*	0.548	0.894	0.000***	0.716	0.697	36.598
PSO	0.482	0.033**	0.547	0.953	0.001***	0.721	0.702	37.463
MPO	0.360	0.011**	0.975	0.458	0.000***	0.505	0.471	14.779
CPO	0.972	0.083*	0.557	0.844	0.000***	0.704	0.684	34.523
PPO	0.071*	0.011**	0.263	0.732	0.001***	0.722	0.702	37.582
RPO	0.000***	0.000***	0.154	0.002***	0.000***	0.344	0.299	7.619
RPSO	0.053*	0.000***	0.090*	0.699	0.000***	0.644	0.619	26.220
RMPO	0.013**	0.596	0.161	0.011**	0.013**	0.197	0.141	3.553
RCPO	0.315	0.000***	0.136	0.093*	0.000***	0.869	0.860	96.092
RPPO	0.000***	0.082*	0.070*	0.002***	0.000***	0.399	0.358	9.633
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$								

Table 16. Immediate Impulse Response of Sales Performance to Independent Variables

	SVO	AVN	AFS	RRV
PO	166.665*	119.758*	33.420	-51.762
PSO	209.369*	200.949**	62.405	-46.191
MPO	16122.380**	15651.080***	-1183.621	-4535.119
CPO	160.465**	107.479*	27.386	-51.510
PPO	278.279*	362.934**	151.142	-19.867
RPO	0.004***	0.003***	0.000	0.003***
RPSO	0.000	0.003***	0.002*	0.001
RMPO	0.018***	0.005*	0.000	0.006*
RCPO	-0.001	0.004***	0.001	0.002**
RPPO	0.002	0.004***	0.000	0.004**
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$				

Table 17. Accumulated Impulse Response of Sales Performance to Independent Variables

	SVO	AVN	AFS	RRV
PO	390.832	2565.052*	1005.832	645.456
PSO	633.563	3532.484**	1425.188	830.350
MPO	68961.830	112611.200*	35582.290	14181.900
CPO	398.414	2337.855*	899.091	571.914
PPO	938.061	5844.872*	2698.055	1459.697
RPO	0.005***	0.005**	0.002	0.004**
RPSO	-0.005	0.036***	0.012	0.017*
RMPO	0.021*	0.012	-0.008	-0.002
RCPO	-0.019	0.056**	0.017	0.029*
RPPO	0.004	0.025**	0.006	0.011
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$				

Table 18. Generalized Forecast Error Variance Decomposition (GFEVD) of Sales Performance

	SVO	AVN	AFS	RRV
PO	9.662	14.683	0.120	0.143
PSO	5.748	16.972	0.167	0.159
MPO	3.695	22.833	0.034	0.466
CPO	9.556	15.024	0.115	0.141
PPO	3.178	23.021	0.809	0.168
RPO	5.592	1.003	0.756	1.832
RPSO	1.220	21.993	1.508	0.150
RMPO	0.489	4.445	0.666	1.530
RCPO	9.920	16.482	2.064	2.400
RPPO	1.009	16.335	1.133	2.864
Average	5.007	15.279	0.737	0.985

Table 19. Comparison Test

	SVO	AVN	AFS	RRV
SVO		-3.876***	3.509***	3.173**
AVN	3.876***		6.244***	5.725***
AFS	-3.509***	-6.244***		-0.900
RRV	-3.173**	-5.725***	0.900	
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$				

4.6 Discussion of Different Sales Performance Metrics

Based on our main empirical results, we now discuss the different impacts of visit behavior on different aspects of sales performance. First, we divided our sales performance into Group 1 (ratio measurements including RPO, RPSO, RMPO, RCPO, and RPPO) and Group 2 (others, including PO, PSO, MPO, CPO, and PPO) and then analyzed the different effects of visit behavior on these two groups of sales performance metrics.

The results of the Granger test and the impulse response functions indicate that AVN is significantly related to most sales performance metrics and contributes to the largest part of all sales performance metrics; there are no major, obvious differences in the two groups of dependent variables. In Table 5, the main empirical results show that SVO strongly affects only PPO and RPPO, while, as shown in Table 6, SVO has a nonsignificant relationship with most of the ratio measures of Group 1 (RPO, RPSO, RCPO, RPPO) and a significant relationship with the dependent variables of Group 2 (PO, PSO, MPO, CPO and PPO) in the short term. In Table 8, SVO also explains a larger proportion of the variance in the sales performance metrics of Group 1 (PO, PSO, MPO, CPO and PPO) than it does in the ratio measurements of Group 2. For example, SVO accounts for 10.546% of PO variance, while it only represents 6.840% of the RPO variance.

RRV and AFS perform very similarly in the two groups of sales performance variables and they both have a significant relationship with the sales performance metrics in the Group 2 ratio measures. The Granger test results show that RRV is significantly related to RMPO, RCPO, and RPPO; AFS is also significantly related to RPO and RCPO; and neither RRV nor AFS have a significant relationship with the Group 1 variables. The immediate impulse response results show that RRV significantly affects RPO, RMPO, RCPO, and RPPO and that AFS significantly affects RPSO. The generalized forecast error variance decomposition (GFEVD) results of Table 8 indicate that RRV and AFS explain a larger proportion of the sales performance measurements in Group 2 versus those of Group 1. For example, in the generalized forecast error variance decomposition (GFEVD) of PPO and RPPO, RRV explains 2.487% of the variance in RPPO but only 0.077% of the variance in PPO. Also, AFS accounts for 1.251% of the variance in RPPO but only 0.706% of the variance in PPO.

AST significantly relates only to RMPO in the Granger test and has a strong relationship with all dependent variables in Group 1 (PO, PSO, MPO, CPO, and PPO) as well as with RMPO in the short term. However, in the GFEVD analysis, AST explains more of the variance in the sales performance metrics of Group 2 than Group 1. Finally, AFP is not significantly related to most dependent variables and does not have a strong relationship with the sales performance measurements between the two groups.

In conclusion, we find that AVN and AFP differ in their effect on sales performance metrics. AVN is significantly related to all dependent variables, while AFP is not significantly related to most variables. RRV and AFS have a much stronger relationship with sales performance metrics in Group 2 in both the Granger test and the impulse response result, and also explain a larger proportion of the variance of sales performance metrics of Group 2. However, SVO and AFS both have a strong relationship with sales performance measurements of Group 1 in the short term but they perform much differently in the GFEVD analysis. SVO accounts for a larger proportion of the variance in dependent variables of Group 1, while AFS accounts for a larger proportion of the variance in the dependent variables of Group 2.

4.7 Discussion on Generalizability

The main limitation of our study is its generalizability: we focus on store-level research and collect data from a single online store on the Tmall platform, which mainly focuses on pharmaceutical and medical equipment products. We acknowledge that there may be differences related to different platforms and different stores due to a focus on different product categories or other reasons. However, our study specifically investigates the relationship between visit behavior metrics and sales performance and compares the impacts of different visit behavior metrics on the online store's sales performance, which can be generalized, at least to some extent. In terms of the strong relationship between visit behavior and sales performance revealed by our study, we think our results are robust across different e-commerce platforms and different stores based on the following reasons.

First, we choose one of the most popular and widely used e-commerce platforms: Tmall. Approximately 150,000 international brands sell millions of products on the platform. On November 11, 2018, its total sales reached nearly 213 billion yuan. According to Alexa statistics (https://www.alexa.com/topsites), Tmall was ranked as the eighth most visited website in the world in April 2019. Thus, we believe that Tmall is a representative e-commerce platform for the purposes of our research. Second, although the online store we used mainly sells pharmaceutical and medical equipment products, this study focuses on the store level; the store has many different products and registers significant online traffic. The average number of store visitors per day is nearly 100,000, and the average number of products sold is about 13,000 per day. The online store is a typical example for the Tmall platform, which is designed mainly for brand retailers; most stores have many different products and significant online traffic. Since the store we used is large, there may be smaller effects derived from specific products and consumers. Finally, based on the available data, we checked the consistency of our results. We included an additional test using variables from the homepage and product pages and conducted a robustness check by removing some independent variables, which indicates the consistency of our results to a certain extent.

In summary, although our study has some limitations, it is robust across different platforms and different stores to some degree in that our study reveals a strong relationship between visit behavior metrics and store sales performance. In Section 5.3 we further address this limitation and make recommendations for how future studies could evaluate the generalizability of our findings by extending our study across different platforms and/or stores.

5 Conclusion

Online shopping has become increasingly ingrained in people's daily lives and represents an important market in the global economy. Accordingly, the factors that influence online shopping have become an important research topic. In this study, we focus on the influence of visit behavior. We analyze visit behavior variables for online stores, including number of visitors, average number of visits, average length of stay time, average number of favorite store links, average number of favorite product links, and ratio of regular visitors. We adopt the VARX model to investigate the dynamic relationships between these visit behavior variables and sales performance. Our findings indicate that these variables have a strong and predictive influence on sales performance, as reflected in the empirical results, additional tests, and robustness check. We use the generalized forecast error variance decomposition method to identify the importance of different metrics. The average number of visits for each visitor is the most important factor affecting sales performance, followed by the number of visitors. Collectively, these findings provide novel implications, both for theory and practice.

5.1 Theoretical Implications

The present study contributes three major theoretical insights to the literature. First, our study contributes to the visit behavior literature by constructing a complex and comprehensive research model that investigates the different aspects of visit behavior, such as number of visitors, repeat visits, visit duration, visitor bookmarking behavior, and visitor attributes. The existing visit behavior research mainly models consumer visit behavior and examines visit behavior based on consumer questionnaires or real-time web traffic data, which largely focuses on limited aspects of visit behavior and fails to explore the impact of visit behavior from a comprehensive viewpoint (Mallapragada et al. 2016; Moe & Fader, 2004a; Roy et al., 2014). In contrast, we collect data from a real online store, and by controlling other factors, we adopt one empirical model that includes different variables of visit behavior, such as number of visitors, average visit numbers for each visitor, average visit duration, average number of favorite store links for each visitor, average number of favorite product links for each visitor, and ratio of regular visitors.

Second, to the best of our knowledge, our study is the first to reveal the associations between six visit behavior metrics and ten sales performance variables based on real online store traffic and sales data. The existing literature uses primarily survey or web traffic data to examine one or two aspects of visit behavior (Lin et al., 2010; Rishika et al., 2013). In contrast, we collect data from one online store, construct six visit behavior metrics, and investigate the relationships to sales performance.

Third, our study contributes to previous e-commerce research on sales performance by comparing the relative importance of different visit behavior metrics. Unlike most of the sales performance literature that focuses on the significant factors of online reviews (Berger et al., 2010; Lin & Wang, 2018; Tang et al., 2014), we compare the importance of different visit behavior metrics in explaining sales performance measures based on the generalized forecast error variance decomposition. We also test the significance of the comparison between two measures, and the results indicate that the average visit number and number of visitors are the most important factors for sales performance among the different variables. This study will hopefully motivate researchers to pay greater attention to the specific important factors influencing sales performance.

Fourth, our study enriches the visit behavior and sales performance literature by providing a unique perspective on how visit behavior variables influence sales performance dynamically. Unlike previous research that mostly uses static methods or data to examine this relationship (Mallapragada et al., 2016; Roy et al., 2014), our study adopts a time-series model (VARX) to investigate the dynamic influence of visit behavior metrics on store sales performance. We not only demonstrate the significant effect of independent variables on sales performance, but also examine the immediate and accumulated influence of visit behavior metrics on sales performance, examined through a unit shock on the independent variables.

5.2 Practical Implications

In addition to the theoretical contributions discussed above, the results of our study yield some important practical implications. First, online store managers should focus not only on online reviews but also on the visit behavior of consumers, as there is a significant relationship between visit behavior and store sales performance. Visit behavior consists of different aspects including number of visitors, repeat visits, visit duration, visitor bookmarking behavior, and visitor attributes. Online store managers are advised to observe changes in visit behavior carefully and use them to develop appropriate operation strategies.

Our study reveals significant positive impacts of the average visit number and number of visitors on the sales performance of online stores; these two metrics were found to be the most important factors affecting the sales performance of online stores. Thus, managers should adopt operation strategies to attract more visitors and increase repeat visits, which may increase store sales. Strategies may include more advertisements to attract higher numbers of new visitors or providing better or personalized services in online stores to retain customers and attract more repeat visits from regular customers.

Analyzing the immediate and accumulated effects of visit behavior metrics will alert managers to possible changes in future sales performance. As reported in Section 4.2, the average visit number of each visitor can significantly increase the sales performance both in the short- and long-term, and an unexpected increase in the average visit number can predict a surge in the number of paid orders by 130.853 in the short-term and 2650.553 in the long-term. Moreover, our study also highlights the importance of the number of visitors to the product page and the average visit number to both the homepage and product page. To increase profits, managers should pay close attention to these factors and introduce strategies such as improving product presentation and mining online reviews and bestseller products for insights.

Finally, our study also provides a novel perspective for investors that can help them better evaluate company performance, potentially leading to better investment decisions. The sales performance of online stores can be affected by consumer visit behavior. Given the current availability of web traffic data, tracking visit behavior could provide insights regarding sales performance in e-commerce, thus offering potential investors additional information.

5.3 Limitations

As discussed above, this study has limitations related to our investigation of a single online store on a single platform, which could be mitigated by future studies that collect data from different stores on the same e-commerce platform or similar stores on different platforms to explore the platform effect and/or store effect. To bolster our findings, future research could also collect data focusing on a certain product and examine visit behavior based on a product category. Another research avenue would be to explore different visitor characteristics, examining, for example, different sales impacts based on personal computer users versus mobile device users. Other ideas include exploring the influence of different product page designs on sales performance, or, in a slightly different vein, investigating whether factors such as cursor movement, cursor speed, and scrolling activities are related to sales performance in online stores.

Acknowledgments

The authors are grateful for the constructive comments of the referees on an earlier version of this paper. This study was supported in part by Fundamental Research Funds for the Central Universities (YJ201950), MOE (Ministry of Education in China) Project of Humanities and Social Sciences (20XJC630003), and National Natural Science Foundation of China (71932002).

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Appendix

Table 20. Lag Length Selection

	PO		PSO		MPO		CPO		PPO	
Lag	**FPE**	**SIC**	**FPE**	**SIC**	**FPE**	**SIC**	**FPE**	**SIC**	**FPE**	**SIC**
0	1.75E-23	-23.13	3.23E-23	-22.52	1.29E-19	-14.23	1.57E-23	-23.24	8.70E-23	-21.53
1	7.20E-26*	-26.85*	1.39E-25*	-26.19*	5.80E-22*	-17.86*	6.54E-26*	-26.95*	4.04E-25*	-25.13*
2	1.06E-25	-24.71	2.10E-25	-24.03	7.58E-22	-15.84	9.58E-26	-24.81	6.11E-25	-22.96
3	1.57E-25	-22.57	3.13E-25	-21.89	1.06E-21	-13.76	1.43E-25	-22.67	9.22E-25	-20.81
4	2.42E-25	-20.43	4.84E-25	-19.73	1.68E-21	-11.58	2.20E-25	-20.52	1.46E-24	-18.63
5	3.72E-25	-18.32	7.54E-25	-17.61	2.57E-21	-9.48	3.40E-25	-18.41	2.12E-24	-16.58
6	5.83E-25	-16.23	1.18E-24	-15.53	4.06E-21	-7.38	5.33E-25	-16.32	3.29E-24	-14.50
7	8.36E-25	-14.30	1.70E-24	-13.59	5.34E-21	-5.54	7.71E-25	-14.38	4.95E-24	-12.52
8	1.02E-24	-12.60	2.18E-24	-11.84	7.41E-21	-3.71	9.54E-25	-12.67	6.12E-24	-10.81
	RPO		**RPSO**		**RMPO**		**RCPO**		**RPPO**	
Lag	**FPE**	**SIC**	**FPE**	**SIC**	**FPE**	**SIC**	**FPE**	**SIC**	**FPE**	**SIC**
0	5.90E-33	-44.94	6.57E-33	-44.84	6.09E-32	-42.61	6.33E-33	-44.88	1.43E-32	-44.06
1	2.00E-35*	-48.86*	3.14E-35*	-48.41*	4.03E-34*	-45.85*	1.35E-35*	-49.25*	9.15E-35*	-47.34*
2	2.39E-35	-46.92	3.76E-35	-46.47	5.78E-34	-43.74	1.90E-35	-47.16	1.37E-34	-45.18
3	3.28E-35	-44.87	5.42E-35	-44.36	7.85E-34	-41.69	2.63E-35	-45.09	1.70E-34	-43.22
4	5.37E-35	-42.66	9.00E-35	-42.14	1.22E-33	-39.53	4.42E-35	-42.85	2.63E-34	-41.07
5	9.08E-35	-40.45	1.45E-34	-39.98	1.82E-33	-37.45	7.09E-35	-40.70	3.95E-34	-38.98
6	1.36E-34	-38.41	2.08E-34	-37.99	3.12E-33	-35.28	1.07E-34	-38.65	6.14E-34	-36.91
7	1.95E-34	-36.48	3.21E-34	-35.98	4.42E-33	-33.36	1.55E-34	-36.71	9.15E-34	-34.93
8	2.77E-34	-34.63	4.61E-34	-34.12	5.27E-33	-31.68	2.14E-34	-34.89	1.25E-33	-33.12

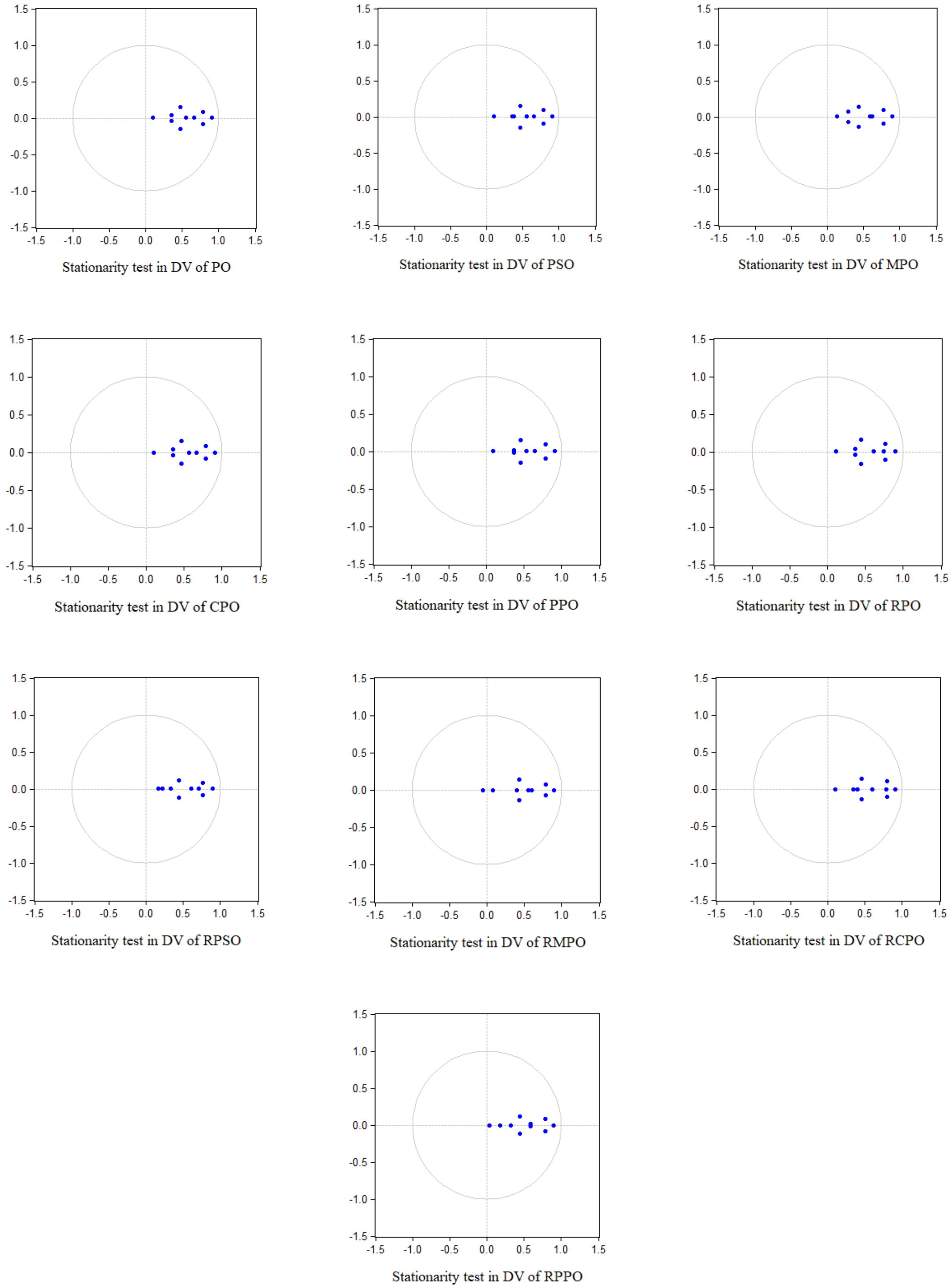

Figure 4. Model's Stationarity Test

Table 21. Johansen Tests for Cointegration

	PO	PSO	MPO	CPO	PPO	RPO	RPSO	RMPO	RCPO	RPPO
0	419.4***	421.8***	428.8***	418.3***	427.1***	417.7***	413.1***	437.2***	411.0***	429.5***
1	332.7***	335.5***	344.0***	331.9***	341.5***	332.1***	330.2***	336.9***	324.9***	345.1***
2	254.6***	259.4***	265.2***	253.9***	266.4***	254.4***	254.2***	255.0***	246.1***	267.3***
3	187.0***	191.4***	191.2***	186.5***	198.2***	188.1***	185.8***	183.8***	179.1***	193.9***
4	134.9***	138.0***	131.6***	133.8***	139.4***	123.9***	122.8***	128.3***	117.5***	126.5***
5	86.4***	87.7***	87.3***	86.1***	88.5***	85.3***	86.9***	84.2***	82.1***	87.4***
6	57.3***	57.7***	60.7***	57.2***	58.7***	56.0***	58.2***	58.6***	52.8**	60.2***
7	35.9***	36.1***	39.7***	35.8***	37.0***	33.343**	35.6***	36.2***	30.2**	37.5***
8	18.8**	18.7**	20.0***	18.8**	18.8**	19.3**	19.2**	17.9**	17.6**	17.9**
9	6.4**	6.3**	7.2***	6.5**	6.3**	7.0***	7.0***	6.0**	6.8***	6.6***
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$										

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